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STUDENT CLASSIFICATION IN HIGHER EDUCATION: LITERATURE REVIEW OF MODELS, APPROACHES, AND CHALLENGES

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ABSTRACT

This paper explores student classification in higher education, addressing gaps in how diverse student characteristics are integrated into classification models. It focuses on personality traits, learning styles, achievement emotions, and player typologies, offering a structured review of how these characteristics are used to define student types. The aim is to support efforts toward personalized learning, early identification of at-risk students, and improved academic support systems. A qualitative, literature-based approach is employed to analyze student classification models and techniques. The paper reviews academic works across various contexts, examining how different student characteristics are used, what classification methods are applied (e.g., machine learning, ontology-based), and the models' educational settings. Key strengths, limitations, and trends are synthesized. The review finds that existing works often lack consistency, generalizability, and holistic integration of student characteristics. Many approaches rely on learning theories or algorithmic techniques without offering comprehensive, scalable solutions. A shift toward multi-dimensional, adaptive models is evident, though ethical, technical, and contextual challenges persist. This study offers a structured synthesis of student classification literature, organized around four key dimensions of student characteristics. It differs from previous reviews by detailing specific models, their applications, and associated student types. The findings contribute to the advancement of ethical and adaptive classification systems and identify future research directions for developing more effective and equitable educational technologies.

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KEYWORDS: Higher Education, Student Classification Models, Personality Traits, Learning Styles, Achievement Emotions, and Player Typologies.

1. INTRODUCTION

In today's educational environment, understanding and addressing student needs is essential for fostering student development, achievement, and success [2, 14, 40]. In this regard, student classification in higher education plays a critical role in personalizing learning, identifying at-risk students, and optimizing academic support systems to better meet individual needs [39]. With the integration of digital education systems [1, 3, 28, 42] and artificial intelligence (AI) [17, 34, 35], and the adoption of student classification systems, modern education is becoming more efficient and data-driven, leveraging predictive analytics, adaptive learning [16, 23], and real-time interventions to enhance student outcomes [20, 26, 27].

In the literature, various models and approaches have been introduced and deployed to classify students based on different factors such as engagement patterns, learning styles, and academic performance [10, 33, 37]. This classification assists teachers to customize resources, interventions, and instructional strategies to better address students' needs. However, despite the expanding research in this area, challenges remain concerning the accuracy, scalability, and ethical considerations of student classification systems.

In the next subsection, we present the relevant literature reviews that have explored this topic.

1.2. Related Works

In [37], the authors have provided a review of related works on the topic of student profiles. Their findings highlight the following points: i) Student classification was largely grounded in learning theories; ii) Student profiles analysis primarily focused on aspects such as learning styles, academic performance, motivation, and learning anxiety; iii) E-learning platforms used for data collection were classified into two categories: adaptive learning styles and intelligent learning styles; iv) Computational approaches, including Bayesian networks and decision trees, were commonly employed to detect student profiles.

This review has briefly discussed various student models, with particular emphasis on the Felder and Silverman model, where the authors have presented and detailed the related student types.

In [18], the authors have reviewed related works to the topic of student profiling, focusing on two main axes; the student classification approaches, and the used characteristics. The survey has shown that a large number of related works have used machine learning (ML) and ontology-based approaches for modelling student profiles. It has also highlighted that personal identity information, academic performance, and learning behaviours have been the most commonly considered features in the literature. Additionally, the authors have proposed a taxonomy of student characteristics for profile modelling, covering various perspectives on the student. However, the paper has not detailed specific student models and associated types that have been presented and deployed in the literature.

The work in [9] has presented student modelling approaches from the literature, along with considered student characteristics, such as knowledge, learning styles, preferences, and motivation. However, similar to previous studies, this survey has not provided consistent student models or types.

1.3. Contributions

In light of the aforementioned related reviews, the contributions of this paper are:

- Unlike previous literature reviews, this paper focuses on four key aspects of student characteristics to present and elaborate on the various student types introduced in the literature. **These aspects are** i) Player Typology, ii) Personality Traits, iii) Learning Style, and iv) Achievement Emotion.
- For each aspect, we present the key classification models and the corresponding student types, highlighting the specific characteristics of each student type.
- In addition, for each classification model, we review related works from the literature, providing information and details on the considered course, the country of the education system, and the classification approaches and techniques employed.
- Moreover, for each related work, we highlight and analyze its key advantages and limitations.
- Finally, a comprehensive list of challenges and future directions, within the topic of student classification in higher education has been provided.

1.4. Paper Organization

The remainder of this paper is organized as follows: First, the used review method is presented in Section 2. Then, Sections 3, 4, 5, and 6 present key student classification models for the aspects of Player Typology, Personality Traits, Learning Style, and Achievement Emotion, respectively. For each model, the corresponding student types are described, and related works are reviewed. In particular, the used classification approaches and techniques are presented, and the corresponding advantages and limitations are discussed. Then, highlighted key points in the presented related works are discussed in Section 7. In Sections 8 and 9 comprehensive lists of challenges and future directions are provided, respectively. Finally, conclusions are drawn in Section 10.

2. REVIEW METHOD

As outlined in the introduction, a comprehensive review of student classification in higher education has not yet been provided in the existing literature. In response, this paper offers an in-depth literature review on the topic, employing a 10-step methodology, which is detailed in this section.

As presented in Figure 1, the used literature review method consists of 10 steps

- Step 1: Define the Main Topic: The first step consists of identifying the main topic of the paper, which revolves around student classification in higher education.
- Step 2: Conduct a Comprehensive Literature Search: It involves collecting a broad range of relevant sources using keywords related to models, approaches, and challenges, within the context of student classification in higher education.
- Step 3: Select and Evaluate Sources: In this step, only credible and reliable sources based on publication quality and research rigor have been considered.
- Step 4: Organize The Literature: The selected sources/ works have been organized in this step, chronologically, thematically, and methodologically.
- Step 5: Read and Analyze: For each related work, the corresponding details, advantages and limitations have been investigated in this step.
- Step 6: Develop logical Structure: In this step, a coherent outline for the review has been fixed, including the related works, the relevant research attempts, the corresponding open problems and challenges, as well as relevant future directions.
- Step 7: Write Clearly and Critically: This step consists of presenting the relevant details and analysis in a clear, precise, and engaging manner, providing critical insights rather than just summaries.
- Step 8: Provide synthesis and Perspective: It aims at offering a comprehensive view, by integrating findings from various sources, highlighting trends and future research directions.
- Step 9: Revise and Refine: This step consists of revisions, ensuring clarity, coherence, and alignment with the main topic and objectives.
- Step 10: Seek Feedback: Finally, comments/suggestions from peers and experts have been considered to enhance the quality of the review.

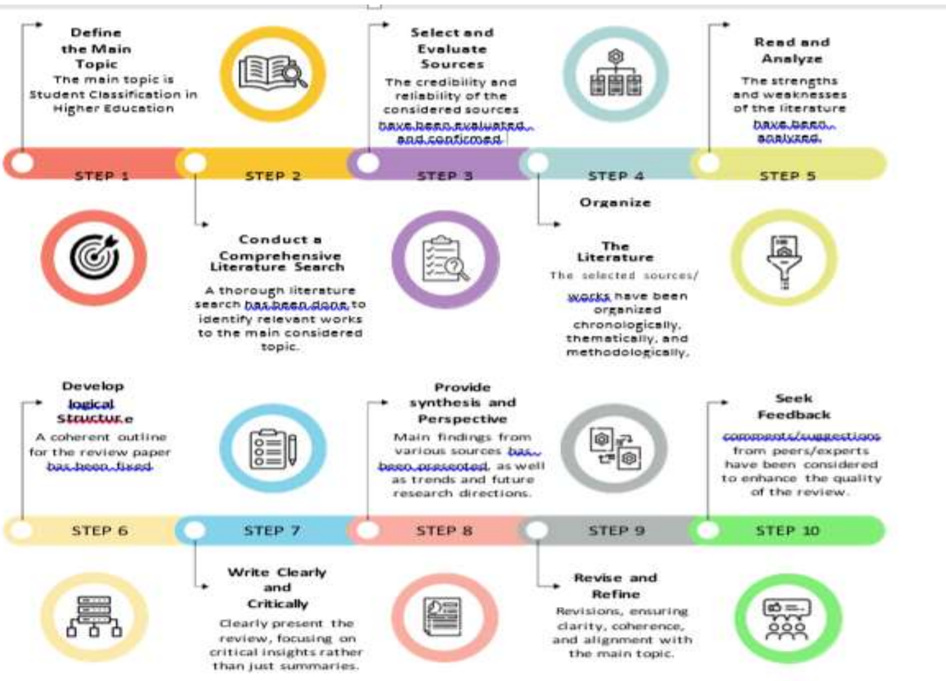

Figure 1: Literature Review Method Consists of 10 Steps.

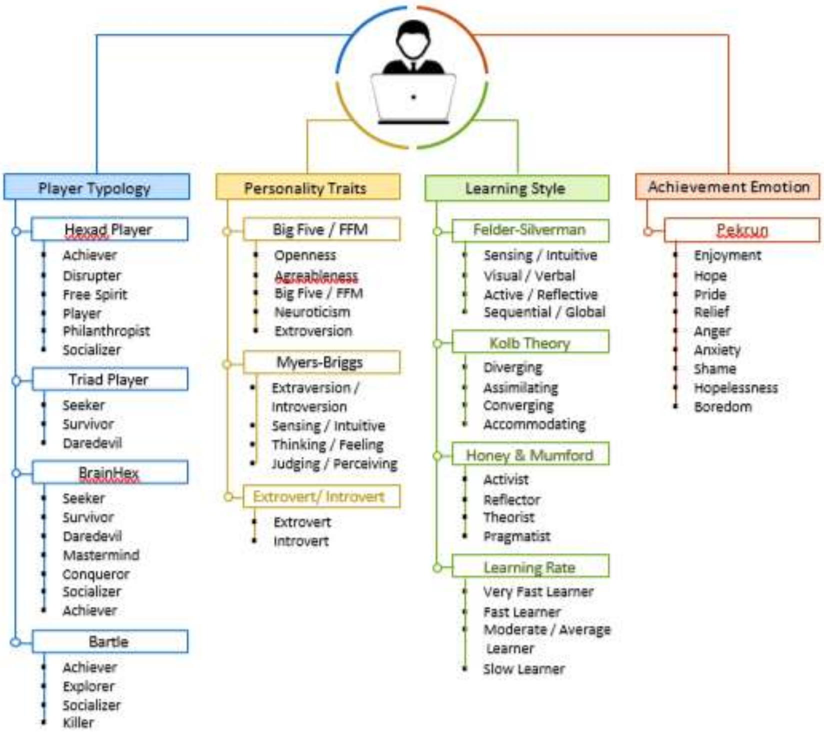

Figure 2: Student Classification, Using Aspects of Student Characteristics.

Based on this review methodology, Sections 3 to 6 present and analyze key student classification models across four main dimensions. Fig. 2 illustrates the four main dimensions (aspects) of student characteristics that have been widely considered in the literature for designing or modeling student types [38], namely, Player Typology. Personality Traits. Learning Style, Achievement Emotion. These aspects are explored through a combination of pedagogical classification approaches rooted in educational theory and data-driven models that leverage empirical behavioral or performance data to infer and validate student types.

Table 1: Related Works to Player Typology-based Student Classification-Part I.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Hexad Player	Achiever Disruptor Free Spirit Player Philanthropist Socialiser	[43]	2016	N/I	Canada	Hexad User Types Survey, Factor & Test-Retest Reliability Analysis	+ The use of test-retest reliability analysis. + Factor analysis has been used to investigate the correlation between the Hexad user types and the Big Five personality traits. - The Hexad survey is not an effective app-roach for automatic student classification.
		[7]	2019	Educational Science	N/I	Paper Based & Online Questionnaires	+ Considering the correlations between gamification user types and mechanics, as well as online learning activities - The Hexad survey is not an effective app-roach for automatic student classification.
		[39]	2021	Introductory Programming	New Zealand	Hexad User Types Survey	+ The study was con- ducted on a significant data set with 1026 students . - The Hexad survey is not an effective app-roach for automatic student classification.
Triad Player	Achiever Disheartened Underachiever	[5]	2014	Multimedia Content Production	Spain	XP-based Gamified Learning	+ The use of cluster analysis − A small sample size − Inconsistency of XP Metric
N/I: Not Indicated, XP: Experience Points							

3. PLAYER TYPOLOGY-BASED STUDENT CLASSIFICATION

This section presents the key student classification models and types related to player typology. Various models have been proposed in the literature to classify students based on this aspect. In the following, we present the key models identified in the literature, which are summarized in Tables 1 and 2.

3.1. Hexad Player Model

The Hexad Player model has been widely applied in the literature [7, 39, 43]. It was originally introduced by Marczewski in [30] as a framework to understand user motivation in gamified systems. The model has proven valuable in educational and digital environments by guiding the design of personalized engagement strategies. However, its generalizability is limited, as it may not fully capture domain-specific or cultural variations. Moreover, its dependence on self-reported questionnaires can affect the accuracy of user classification. **The model aims to classify the users into six types**

- Achiever: Driven to showcase their skills, this student prioritizes efficient and effective task completion, leading to increased productivity and personal growth.
- Disruptor: This student aims to disrupt the system, motivated by a desire to instigate change. He actively challenges established norms and advocates for new ideas.
- Free Spirit: He seeks independence and freedom in his education, valuing a personalized learning style that challenges traditional methods and promotes authentic self-expression.
- Player: Motivated by external rewards, this student puts in extra effort, leading to improved academic skills, a deeper understanding of the material, and a greater enthusiasm for learning.
- Philanthropist: Driven by a sense of purpose, this philanthropist is willing to give without expecting any reward. Their commitment to helping others inspires positive change and encourages acts of kindness.
- Socialiser: Motivated by the desire for social connections, this student builds relationships with classmates and teachers, enhancing their sense of belonging and enhancing the overall learning experience for all.

These six student types has been considered in [43]. In particular, the authors have introduced a 24-items survey response scale to assess students' preferences across the six user types in the Hexad framework. In addition, they have conducted internal and test-retest reliability analysis, as well as factor analysis, to validate the presented scale. Furthermore, additional analysis revealed significant associations between the Hexad user types and the Big Five personality traits.

The results offer significant potential for customizing games or gamified learning, as they are grounded in player

Motivations specific to these applications. However, using the Hexad survey only is not an effective approach for automatic classification of students.

Table 2: Related Works to Player Typology-based Student Classification-Part II.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Brain-Hex	Seeker - Survivors - Daredevil - Mastermind - Conqueror - Socializer - Achievers	[22]	2018	French Spelling & Grammar	France	BrainHex Questionnaire	+ The involvement of gamification experts. Automated person- alization of gaming features for different learners − Reliance on self- reported data. − Small sample size. − Potential participant bias.
Bartle	Achiever - Explorer - Socializer - Killer	[32]	2024	N/I	Iran	Bartle Player Styles Questionnaire & MANCOVA Data Analysis Method	The use of MANCOVA data analysis technique. - The presented classification method is focusing only on Explorer and non explorer students.
/I: Not Indicated, MANCOVA: Multivariate Analysis of Covariance							

In the same context, the work in [7] has introduced both paper-based and online questionnaires to classify bachelor's and master's students in educational science, using the six Hexad player types framework. This work has presented a notable strength in exploring the correlations between gamification user types, mechanics, and online learning activities. However, the use of the Hexad survey cannot be considered as an ineffective approach for the automatic classification of students.

In [39], a personalized gamification approach in an introductory programming course has been introduced. The approach consists of conducting Hexad survey of 24 questions to measure students' preference for different elements in a gamification environment. The study was conducted on a significant data set with 1026 students. By analyzing the responses to these questions, the students were classified to six hexad user types. After investigating and analyzing the data of Hexad survey, the authors have concluded that using only the Hexad survey is not an effective approach for automatically classifying students or personalizing gamification.

3.2. Triad Player Model

This student classification model has been introduced in [5], where the authors have presented a comprehensive analysis of student data from an experience points (XP)-based gamified Multimedia Content Production (MCP) course.

The model effectively captures temporal engagement patterns and offers valuable insights into how students interact within gamified learning environments. However, relying on only three types may oversimplify the diversity of student behavior and overlook deeper motivational factors. Based on their analysis, the authors identified distinct behavioral patterns in student performance throughout the semester, **classifying them into three types**

- Achiever: These students consistently earned top grades, attended nearly all classes, and actively engaged with the course material. They thrived on competition, viewing the course as a challenge, which enhanced their motivation and made learning more enjoyable.
- Disheartened: This student category shows average-to-low grades and underachievement, despite high attendance and downloading course materials. Initially competitive with better-performing peers, they struggled in online assessments, indicating decreased proactivity and engagement over time.
- Underachiever: These students has the lowest grades and attendance, showing minimal engagement by downloading the fewest course materials and participating less than their peers. Their overall lack of motivation suggests they see the course as an obligation rather than a chance for achievement.

Accordingly, the authors have provided personalized guidelines for designing gamified learning experiences that meet the needs of this different student types.

This work offers several advantages. One key strength is the use of cluster analysis, which has provided structured insights into student performance and gaming habits, revealing distinct student profiles. Additionally, the study has highlighted meaningful gender-based differences in gaming behaviors and academic performance, offering valuable implications for the design of more inclusive and effective educational games.

However, the study has several limitations. The small sample size, with clusters as small as seven students, has restricted the ability to generalize the findings and may have led to inconclusive results. Furthermore, the study has been limited to a specific MSc course, reducing its applicability to other educational contexts or disciplines. Additionally, more data is needed to better understand the needs of certain student types, particularly the Disheartened and Underachiever students, as the XP metric has lacked consistency in these cases.

3.3. BrainHex

The BrainHex category divides learners into seven types based on how they approach learning and what motivates them. It provides a nuanced framework that links game-based motivations with learning preferences, making it useful for designing engaging, personalized educational experiences. However, its reliance on predefined typologies may not fully capture the complexity of learner behavior across different contexts or learning environments. **The BrainHex student types are**

- Seekers: Curious explorers who thrive on hands-on learning and new experiences, inspiring others with their enthusiasm for experimentation and collaboration. They may struggle with routine tasks that lack excitement.
- Survivors: Excel at overcoming challenges, finding motivation in their fears. They thrive in difficult situations, using creativity and determination to turn obstacles into opportunities for growth.
- Daredevils: Thrive on risk-taking and adventure, seeking exciting challenges that push their limits. They excel in hands-on projects and dynamic environments but may disengage in routine settings, needing stimulation to stay motivated.
- Masterminds: Enjoy strategizing and solving complex problems, seeking out challenges that require critical thinking. They benefits from activities that involve planning, strategy development, and intricate problem- solving tasks.
- Conquerors: These students are motivated by

competitive scenarios that allow them to test their skills and showcase their accomplishments against others.

- Socializers: They benefit from activities that emphasize group work and social engagement, enhancing their learning experience through shared experiences.
- Achievers: Motivated by completing tasks and reaching goals, finding satisfaction in their progress and accomplishments. They thrive in structured environments that reward task completion and provide clear milestones.

In [22], the authors have presented a model for automatically adapting gaming features to different learner profiles in educational environments. This model was implemented in a web-based platform designed to teach French spelling and grammar through a personalized gamification approach. The personalized experience was developed using input from gamification experts, alongside the BrainHex questionnaire to identify distinct learner profiles.

The study highlights the innovative adaptation of gaming features tailored to user profiles, effectively boosting motivation and participation by addressing specific needs. Its seamless integration into existing learning systems ensures content and pedagogy remain unaffected. However, the reliance on self-reported data, a small final sample size, and potential participant bias limit the ability to generalize the proposed method.

3.4. Bartle Model

The Bartle Model is a framework developed by Richard Bartle in 1996 to categorize players in video games based on their preferences and motivations. This concept has also been applied to understand the different motivations of students in a gamified learning environment. The model offers a simple yet effective lens for identifying dominant motivational traits, which can inform personalized engagement strategies. However, its binary classification dimensions and fixed four-type structure may limit its ability to capture the full spectrum of student behavior and motivation in educational contexts. **The four primary types are**

- Achievers: These students are motivated by completing tasks, earning rewards, and mastering challenges. They enjoy setting and reaching goals, striving for recognition, and progressing through levels or milestones.
- Explorers: are driven by curiosity and the desire to discover new concepts. They enjoy learning through exploration, experimenting with new ideas, and uncovering hidden aspects of the subject matter.
- Socializers: thrive on interaction and collaboration. They are motivated by engaging with peers, discussing ideas, and working together on group tasks or projects.
- Killers: Competitive and enjoy the challenge of outperforming others. They are driven by the desire to win, demonstrate their skills, and overcome obstacles in a competitive setting.

This model has been used in [32] to classify students into groups based on their player typology aspect. In this work, the Explorer player students formed one group, while students with other types constituted a separate group. All students participated in a pre-learning test, an exploratory-style game, and subsequent learning and retention tests. The data were analyzed using multivariate analysis of covariance (MANCOVA), revealing significant differences between the two student groups. In this work, the authors focus only on explorer and non-explorer students, which presents a limitation of this student classification approach.

4. PERSONALITY TRAITS-BASED STUDENT CLASSIFICATION

In this section, we present three main categories that have been widely used in the literature for personality traits-based student classification. **As shown in Tables 3 and 4, these categories are**

4.1. Big Five/FFM

The Big Five, also known as the Five-Factor Model (FFM), is a well-established framework for understanding personality. It proposes that human personality can be described using five broad categories, each representing a range of traits. This model is widely used in educational research to examine how personality influences learning behavior and academic performance. However, its broad trait dimensions may overlook context-specific behaviors and situational factors, **limiting its precision in modeling individual differences in learning environments. These categories are**

- Openness to Experience: Students high in openness are curious and creative, eager to explore new ideas and approaches. They thrive in environments that encourage innovation and critical thinking.
- Agreeableness: Students high in agreeableness are cooperative and empathetic, valuing teamwork and positive relationships. They contribute to a supportive classroom environment and are often willing to help classmates.

- Conscientiousness: Conscientious students are organized and responsible, demonstrating strong self-discipline in their studies. They excel in structured settings with clear goals and deadlines.
- Neuroticism: Students with higher neuroticism experience emotional instability, especially under pressure. They benefit from supportive teaching practices that help manage stress and enhance their learning experience.
- Extroversion: Extraverted students are sociable and energized by peer interactions, often thriving in group work and discussions. They tend to take on leadership roles and actively participate in classroom activities.

By using this model, the authors in [13] have presented a student classification method based on the Big Five Inventory Questionnaire. This method classified students enrolled in different courses; Object-Oriented Design Methodology, Basic Software, and Information Monitoring Methodology. By analyzing personality traits through the Big Five dimensions, the authors aimed to identify patterns that can predict distinct student types based on the Big Five personality category.

Table 3: Related Works to Personality Traits-based Student Classification Part I.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Big Five / FFM	Openness to Experience - Agreeableness Conscientious- ness - Neuroticism - Extroversion	[13]	2018	Object Oriented Design Methodology Basic Software Information Monitoring Methodology	Tunisia	Big Five Inventory Questionnaire	The classification method considered different courses Small sample size
		[4]	2023	e-Learning Informatics Engineering Courses	Indonesia	Ten Item Personality Measure Questionnaire. Achievement Emotion Questionnaire Learning Activity log k-means algorithm	Real-time data of student's activity. Small sample of only 40 students.
Myers-Briggs	- Extraversion / Introversion Sensing / Intuitive Thinking / Feeling - Judging / Perceiving	[15]	2019	Introduction to Computing Systems and Programming	Iran	Myers-Briggs Type Indicator Questionnaire	+ The study showed improved learner performance by engaging their personality and emotions. − Limited sample size with 43 students.
		[25]	2024	N/I	India	A Designed Questionnaire in Collaboration with a Psychiatrist The Navi bias Algorithm The k-means Clustering Algorithm	The use of pre- existing statistics to correlate personality types with academic performance. − Limited sample size of only 70 students.

N/I: Not Indicated, FFM: Five-Factor Model

Table 4: Related Works to Personality Traits-based Student Classification-Part II.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Extrovert/Introvert	- Extrovert - Introvert	[12]	2018	Object Oriented Design Methodology	Tunisia	Modified Big Five Inventory Questionnaire	+ A clear and scalable model. − Overgeneralization of personality traits. − Small sample size with 57 learners.
		[41]	2018	Programming	Brazil	Big Five Inventory Questionnaire	+ Considering a control and experimental groups to validate the impact of gamification. − Small sample size with 40 participants.

From their findings, the authors were able to identify a pattern between personalities and its preferred game element. Additionally, the study revealed that extraversion, conscientiousness and openness personality traits strongly impacted the reception of the learner to certain game mechanics. However, the paper falls short in its homogeneous small sample size, as the study was only conducted on 105 students. In the same context, Ten-Item Personality Measure (TIPM), a concise version of the BFIQ has been introduced in [4] to classify students enrolled in e-learning Informatics Engineering courses. In addition to TIPM, the authors have deployed the Achievement Emotion Questionnaire (AEQ), a student learning activity log, and the k-means clustering algorithm to identify distinct student types, with the aim of providing a more personalized learning experience.

In this work, the authors' use of a platform to track students' activity provided real-time data, offering valuable insights that complemented the survey results. Additionally the use of personality traits and emotional achievement metrics introduces a user-centric approach to personalize e-learning. However, the paper highlights some limitations, such as the narrow focus on personal characteristics and activities. Additionally, the study was based on a small sample size of just 40 students, which may limit the generalizability of the findings.

4.2. Myers-Briggs

The Myers-Briggs is another popular psychological framework that classifies individuals into 16 distinct personality types based on preferences in four dimensions. It has been widely used to explore learner traits and support personalized instruction by aligning teaching strategies with personality profiles. However, the model has been criticized for its limited empirical support and binary choices within each dimension, which may oversimplify complex personality traits. The four dimensions are:

- Extraversion/Introversion: The extrovert students enjoy engaging in activities, particularly those involving social interaction. In contrast, introverts are reflective thinkers who prefer to focus on problem-solving and often seek solitude to recharge.
- Sensing/Intuitive: Sensing students are detail-oriented, preferring facts and straightforward methods, and they tend to avoid complications when solving problems. In contrast, intuitive students focus on building relationships and connecting various learning patterns, making them adept at discovering, creating, and developing innovative ideas.
- Thinking/Feeling: Thinking students prioritize logic and analytical reasoning in problem-solving, while Feeling students emphasize human values and prefer working in groups of small sizes.
- Judging/Perceiving: Judging students are action-oriented and can make quick decisions and complete tasks efficiently. In contrast, Perceiving students focus on examining details and investigating new insights related to the problem that needs to be solved.

In [15], the authors utilized the Myers-Briggs Type Indicator (MBTI) questionnaire to classify students enrolled in an Introduction to Computing Systems and Programming course. This classification was then incorporated into an adaptive e-learning environment, which the students found more engaging and aligned with their personality traits. Moreover, the system demonstrated a better understanding of students' states, provided more appropriate responses, and contributed to an improved learning rate. This contribution has revealed an overall improvement of the learners' performance by appealing to their relevant personality and emotion. However, the paper falls short in its limited sample size of 43 learners, all of whom were first year students from a single course narrowing down the possibility of the results.

In the same context, the authors in [25] have designed a comprehensive questionnaire in collaboration with a psychiatrist to classify a group of students according to their Myers-Briggs personality types. To ensure data quality, the Navi bias algorithm was employed to filter out irrelevant information. Then, the k-means clustering algorithm was applied to group students into distinct clusters based on shared personality traits. These clusters were then used to predict various aspects of students' behavior, learning styles, and academic performance. The accuracy of these predictions was validated by comparing them with assessments provided by the collaborating psychiatrist. However, the study was limited by the sample size of 70 students. Moreover, most of them were from bachelor of science in electronic engineering.

4.3. Extrovert/Introvert

As a subcategory of the Big Five personality traits, the extrovert/introvert dimension has been used in the literature to classify students into two distinct types

- Extrovert: A student who enjoys engaging in activities that involve social interaction.
- Introvert: A reflective thinker who focuses on finding solutions.

This binary classification helps capture differences in student participation, collaboration preferences, and engagement styles. However, the oversimplified dichotomy may not fully reflect the spectrum of social behavior, as many students exhibit characteristics of both types depending on context.

In [12], the authors have employed a modified version of the Big Five Inventory Questionnaire to classify students enrolled in Object-Oriented Design Methodology course as either extroverts or introverts. The authors have mapped the game elements with the compatible personality, motivating the learner to complete their task. They were able to build a simple model that represented this relationship. However, the contribution falls short in its restriction of looking only at 2 personality traits overlooking other possible traits.

In addition, the sample size for the study was relatively small, consisted of only 57 learners.

A similar methodology was adopted in [31], where students in a programming course were classified as either extroverts or introverts. This work presents significant limitations. Firstly, the binary classification of students into just two personality types extrovert or introvert oversimplifies the complexity of student personality and fails to account for the full spectrum of traits. Moreover, the small sample sizes, 40 participants, in both studies undermine the reliability of their findings, emphasizing the need for larger, more representative samples to ensure a more robust and accurate student classification.

5. LEARNING STYLE-BASED STUDENT CLASSIFICATION

This section outlines four categories commonly employed in the literature for classifying students based on learning style. **As illustrated in Table 5, these categories include**

5.1. Felder-Silverman

The Felder-Silverman Learning Style Model (Felder-Silverman Model, or FSLSM) is a widely used framework for understanding student differences in learning preferences. Developed by Richard Felder and Linda Silverman. It has been extensively applied in engineering and STEM education to support the design of adaptive learning environments and instructional strategies. However, the model's reliance on fixed categories has drawn criticism for lacking strong empirical validation, and it may not fully capture the fluid and context-dependent nature of learning preferences.

Table 5: Related Works to Learning Style-based Student Classification.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Felder Silverman	Sensing/Intuitive Visual/Verbal Active/Reflective Sequential/Global	[46]	2017	Information Technology	Serbia	Modified Felder-Silverman Index Test	+ Applying Personalized Gamification in E-Learning − The proposed solution is not supported by empirical data.
		[19]	2021	Data Base Management System	Pakistan	Felder-Silverman Index Test	+ The use of student interactions on the learning platform. − Limited sample size of 175 students from a single course.
Kolb Theory	Diverging Assimilating Converging Accommodating	[21]	2023	Information Technology	Philippine	J48-Decision Tree Algorithm	+ Significant sample size of 408 students. − The model's complexity may cause practical integration problems due to technical and resource- dependent challenges.
Honey & Mumford	Activist Reflector Theorist Pragmatist	[29]	2023	Newtonian Mechanics	Peru	Case-Based Reasoning Techniques	+ A high classification efficiency. − Limited exploration of prior contributions.
Learning Rate	Very Fast Learner Fast Learner Moderate/Average Learners Slow Learner	[44]	2021	Computer Science Engineering Courses	India	k-Nearest Neighbors	+ A High classification efficiency. + Significant sample size including 313 students. - Categorizing learning rates into fixed groups ignores the potential for change

This model classifies learners based on four dimensions

- Sensing / Intuitive: The sensing students often prioritize practical experience and focus on facts, details, and numbers. In contrast, intuitive students prefer exploring new ideas and tend to engage more with abstract concepts and mathematical theories.
- Visual / Verbal: Visual learners typically prefer methods of conveying information through images, diagrams,
- flowcharts, and timelines. In contrast, Verbal learners favor written and oral explanations, often learning from textual documents, books, and lectures.
- Active / Reflective: Active students enjoy engaging in discussions as part of the learning process, whereas reflective students prefer to think about new information and concepts quietly, often choosing to study or work alone.
- Sequential / Global: Sequential students prefer logical and sequential steps in problem-

solving, while global students start by comprehending the core ideas and main concepts, which allows them to solve problems quickly and creatively.

The Felder-Silverman Index of Learning Styles Test has been used in [46] and [19] to classify students enrolled in IT courses and Database Management Systems, respectively. In [46], the authors applied the classification for personalized gamification in e-learning. However, the proposed solution lacks empirical validation, as it does not provide any supporting data or real-world application results to demonstrate its effectiveness. The authors in [19] used student interactions on the learning platform for personalization. However, the study is limited by a small sample size of just 175 students from a single course.

5.2. Kolb Model

Kolb's Learning Theory, also known as Kolb's Experiential Learning Theory (ELT), is a widely recognized model that emphasizes the role of experience in the learning process. Developed by David A. Kolb in the 1980s, the theory proposes that learning is a continuous cycle consisting of the following four stages, where each stage represents a distinct way of engaging with the learning process. The model has been influential in shaping experiential and active learning strategies across various educational contexts. However, its cyclical structure may not capture the nonlinear and adaptive nature of real-world learning, and its application can be limited by individual and cultural differences in learning preferences. **The learning process within this model consists of**

- Concrete Experience (CE): This stage involves directly experiencing a situation or activity, engaging in hands-on, real-world learning.
- Reflective Observation (RO): After the experience, learners reflect on what happened, analyzing their thoughts and reactions to understand the situation more deeply.
- Abstract Conceptualization (AC): Here, learners form abstract theories or concepts based on their reflections, looking for patterns or general principles that can be applied in the future.
- Active Experimentation (AE): Learners then apply their newly developed theories or concepts in real-world settings, testing out their ideas and making adjustments based on the outcomes.

While these stages describe the process of learning, Kolb also categorizes learners based on their preferences for certain types of learning, which are closely related to the stages. These preferences are often referred to as learning styles and are based on how individuals typically engage with the four stages. **The four main learning styles are**

- Diverging (CE + RO): Learners who prefer to feel and observe, often excelling in brainstorming and idea generation.
- Assimilating (AC + RO): Learners who prefer to observe and think, often excelling in understanding and conceptualizing information.
- Converging (AC + AE): Learners who prefer to think and do, often excelling in problem-solving and applying theories in practical situations.
- Accommodating (CE + AE): Learners who prefer to feel and do, often excelling in hands-on experimentation and active involvement in tasks.

Thus, while the four stages represent different modes of learning, they also connect to these learning styles, which highlight different approaches to processing and using information.

This experiential learning theory has been adopted in [21], where the J48-based decision tree algorithm has been used to classify a set of students enrolled in Information Technology, providing insights into their academic performance and learning style, according to Kolb's theory. The study involved a significant sample size of 408 students. However, the model's complexity may cause practical integration problems, particularly due to technical and resource-dependent challenges.

5.3. Honey & Mumford Model

Honey's Model of Learning Styles, introduced by Peter Honey and Alan Mumford, identifies four key learning styles, each based on how individuals prefer to engage with new experiences and process information. The model has been widely adopted in professional training and education to tailor learning activities to individual preferences. However, similar to other fixed-style models, it has been critiqued for its limited empirical validation and potential to oversimplify the complex, dynamic nature of learning behaviors. **Here's a brief description of each**

- Activist: An activist thrives on new experiences and is excited by challenges. This student type is hands-on, spontaneous, and enjoys being in dynamic environments and is often eager to jump into tasks or projects without overthinking.

- Reflector: A reflector prefers to observe and think through experiences before drawing conclusions. This type is thoughtful and likes to review information from multiple perspectives. A reflector benefits from taking time to analyze and reflect on what they've learned, often seeking feedback to refine their understanding.
- Theorist: A theorist is logical, analytical, and enjoys understanding the principles and theories behind concepts. He prefers structured approaches and value clarity and coherence in learning. A theorist learns best when he can explore concepts in depth and make connections to broader theories.
- Pragmatist: A pragmatist is practical and solution-oriented, preferring to apply knowledge in real-world situations. He focuses on how concepts can be used effectively and is motivated by practical outcomes. A pragmatist excels when he can see how his learning will help solve problems or achieve tangible goals.

Each style reflects a different way of processing information and approaching learning, with an individual often exhibiting a dominant style but also benefiting from using aspects of all four styles in different situations. By using Honey's four learning styles, the authors in [29] have employed the Case-Based Reasoning (CBR) technique to efficiently classify students in a Newtonian Mechanics course.

5.4. Learning Rate Model

This model was adopted in [44] to classify students of computer science engineering, using the k-Nearest Neighbors (k-NN) ML technique.

Table 6: Related Works to Achievement Emotion-based Student Classification.

Model	Student Types	Ref.	Year	Course	Country	Method	Pros & Cons
Pekrun	- Enjoyment - Hope - Pride - Relief - Anger - Anxiety - Shame - Hopelessness - Boredom	[4]	2023	e-Learning Informatics Engineering Courses	Indonesia	Achievement Emotion Questionnaire - Learning Activity log - k-Means algorithm	+ The inclusion of emotions in the userprofiling model. − Small sample size of 40 students. − The solution only captures students' emotional states at specific times, without exploring their evolution.
		[45]	2024	English Language	China	A short Version of Pekrun Achievement Emotions Questionnaire	+ Significant sample size of 380 students. − The use of question-naire only may have lead to skewe results.

This learning rate model classifies students into the following four learner types, based on their ability to grasp and retain new concepts at different speeds. It provides a data-driven approach to identifying learning patterns and informing adaptive instructional strategies. However, the model's focus on speed of learning may overlook other influential factors such as motivation, prior knowledge, and learning context, which are also critical to student performance. **The four learner types are**

- Very-Fast Learners: These students can grasp new concepts quickly and exhibit strong analytical thinking, problem-solving skills, and knowledge retention.
- Fast Learners: Characterized by students who are quick on the uptake, have strong understanding of course material and perform well, academically, but may not possess the same degree of cognitive skills as the very-fast learner type. The majority of the tested engineering students fall within the fast and moderate learner category.
- Moderate/Average Learners: Students who may require additional time and support to fully grasp more complex course material. The majority of tested engineering students fall within the fast and moderate learner category.
- Slow Learners: Despite having difficulty retaining new information and keeping pace with the average pace of instruction, these students can improve their learning rate via additional support (such as rememdial lessons) and self-directed learning.

The model provides a framework for understanding the varying learning speeds within a group and emphasizes the importance of tailored instructional strategies to help each type reach their potential. The model offers high classification efficiency, demonstrated by a significant sample size of 313 students. However, categorizing learning rates into fixed groups may overlook the potential for change and the dynamic nature of student learning patterns.

6. ACHIEVEMENT EMOTION-BASED STUDENT CLASSIFICATION

Achievement Emotion could be considered a distinct aspect of student characteristics, although it is closely related to personality traits. Achievement emotions refer to the emotions students experience in response to their academic activities, particularly those related to success or failure in learning tasks. These emotions include feelings like pride, frustration, enjoyment, anxiety, and disappointment, all of which are commonly associated with achievement-related situations (e.g., completing assignments, receiving grades, or performing on tests). These emotions can significantly influence students' motivation, persistence, and overall learning experience [6].

While achievement emotions are distinct, they are influenced by personality traits. For example:

Emotional stability (a trait within the Big Five personality model) can affect how a student reacts emotionally to academic challenges. Students with high emotional stability may be less likely to experience anxiety or frustration compared to those who score lower in this trait.

Conscientiousness could also influence achievement emotions. A student high in conscientiousness might feel pride when meeting goals but could also experience more frustration if they fail to meet their standards. Self-esteem and self-efficacy, which are often related to personality traits, can also shape how students experience achievement emotions. Students with high self-esteem may experience more pride and satisfaction, while those with low self-esteem may feel more anxiety or shame when facing academic challenges.

However, achievement emotions could still be considered a standalone aspect of student characteristics for several reasons

Context-Specific Achievement emotions are directly tied to academic achievement and performance, whereas personality traits encompass broader and more stable aspects of an individual's behavior across various contexts (not limited to academics).

Unique Impact on Learning Achievement emotions play a unique role in regulating motivation, engagement, and perseverance in learning. They influence how students approach tasks, how persistent they are when facing difficulties, and how they process feedback.

Dynamic Nature Unlike stable personality traits, achievement emotions can fluctuate based on immediate academic experiences [36]. A student might feel motivated and excited (pride) after performing well, or stressed and anxious (frustration) after a poor test result [24]. This dynamic quality of emotions may warrant their consideration as a separate factor.

Hence, while achievement emotions are related to personality traits, particularly in how students emotionally respond to academic challenges, they could be considered a distinct aspect of student characteristics due to their specific role in learning motivation, engagement, and academic performance. This distinction is particularly useful in the context of understanding how emotions impact learning processes, which is different from understanding more stable personality traits that influence behaviour in general. Therefore, achievement emotions might be better modelled as an additional independent factor, alongside personality traits and other student characteristics.

As shown in Table 6, recent studies have applied the Pekrun model to classify achievement emotions in students across various disciplines. [4] has used the model to classify emotions in students enrolled in an e-Learning Informatics Engineering course, while [45] has explored a shortened version of the Pekrun Achievement Emotions Questionnaire to categorize emotions in students taking an English language course. **In both works, students were classified into nine distinct types of achievement emotions**

- Enjoyment: It happens when students feel happy and satisfied with their learning or success. They find the task fun and rewarding.
- In this case, the student feels excited and positive when he solves a problem or complete a fun project.
- Hope: Hope is when students believe they can succeed in the future. They feel optimistic and expect good things to happen.
- A student feels hopeful before a test, believing he can do well if he keeps working hard.
- Pride: It is felt when students accomplish something important and feel good about their efforts and success. A student feels proud after getting a good grade or finishing a difficult assignment.
- Relief: Relief is the feeling students get when a stressful situation is over and they are no longer worried. A student feels relieved after finishing a tough exam or project.

- Anger: It happens when students feel frustrated or upset, often when things don't go as expected or they feel treated unfairly.
- A student might feel angry if they get a bad grade they didn't deserve or face unfair rules.
- Anxiety: Anxiety is the nervous feeling students get when they worry about failing or not doing well. A student feels anxious before a big test, afraid they might not perform well.
- Shame: It is the feeling of embarrassment when students think they have failed or let themselves or others down.
- A student feels ashamed if he do poorly on a test and worry about how others will see them.
- Hopelessness: Hopelessness is when students feel like they can't succeed, no matter how hard they try. A student feels hopeless if he struggles with a subject and believes he will never improve.
- Boredom It happens when students feel uninterested or unstimulated by what they are doing. They find the task dull or repetitive.

A student feels bored during a long lecture or when doing something that is not engaging. Each of these emotions reflects how students feel while working toward academic goals, whether positive (such as enjoyment or pride) or negative (such as anxiety or hopelessness). However, a key limitation of these contributions is that they often detect emotional states at specific times, without exploring their evolution, presents a limitation of these contributions.

7. DISCUSSION

As presented in the previous sections, the related work on student classification revolves around traditional and AI-driven approaches/models.

Traditional models, such as those based on established psychological or pedagogical theories (e.g., Kolb's Learning Styles, and FSLSM), typically rely on self-reported or observational data gathered through questionnaires or interviews. These models offer high interpretability and strong alignment with educational theory but often suffer from limited scalability, static profiling, and reduced adaptability to changes in student behavior or context. In contrast, AI-driven models leverage machine learning algorithms to uncover patterns in large-scale, multi-modal data sources, including LMS logs, assessment scores, and behavioral interactions. These data-driven methods enable dynamic and fine-grained classification, allowing for real-time adaptation and personalized feedback. However, they may face challenges in interpretability, especially when using complex or black-box models. Overall, the integration of AI-driven approaches represents a methodological shift toward scalable, adaptive, and empirically validated classification frameworks that complement and extend traditional theory-based models.

For both student classification approaches, several key points can be highlighted

(1) Sample Size and Representativeness: Many studies rely on small sample sizes, which limits the ability to generalize their findings in a consistent and representative manner. This also makes it difficult to account for differences across diverse student groups.

(2) Lack of Psychiatric Expertise: The lack of involvement from psychiatric professionals in the development of student classification methods is a significant gap. Integrating their expertise could enhance the validity and trustworthiness of the research.

(3) Methodological Rigor: As detailed in the previous sections, some studies lack a clear and detailed methodology, offering insufficient information on data collection, preprocessing, and validation procedures. This lack of transparency makes it difficult to evaluate the replicability and validity of their findings. Furthermore, the use of advanced ML techniques, such as clustering algorithms or predictive models, is not well considered in the literature, limiting the depth and sophistication of the proposed contribution. Indeed, the literature is rich in works related to student classification using ML techniques [4, 8, 11, 21, 29, 33], offering valuable insights across various educational contexts. However, many of these research efforts fall short in demonstrating rigorous methodological practices, particularly in clearly articulating their experimental setup, feature selection rationale, or validation strategies. This undermines the reliability and generalizability of their findings. The integration of more robust methodological frameworks grounded in both educational theory and data science best practices remains an area for improvement. Our review highlights the need for future studies to adopt transparent, reproducible, and theoretically grounded approaches that fully leverage the capabilities of modern ML techniques.

(4) Limited Validation and Accuracy: Numerous studies and research works lack external validation from experts, such as psychiatrists

or psychologists, which raises concerns about the accuracy and reliability of their findings. The absence of such validation is a common issue in the literature, leading to doubts about the practical use of the proposed student classification approaches.

(5) Limited Research and Need for Improved Student Classification in Programming Education: Research on student classification methods in programming education is still relatively limited. There is a growing need for more effective classification techniques to better assess and support students' programming skills and learning progress. Current studies often lack comprehensive approaches to categorizing students, making it challenging to tailor educational strategies. Incorporating more sophisticated classification methods, such as data-driven models or expert-driven frameworks, could enhance the accuracy and effectiveness of student assessment, ultimately improving learning outcomes in programming education.

8. CHALLENGES

Building efficient and robust student classification models requires tackling a range of challenges, from integrating di- verse data sources to ensuring data quality, privacy, and scalability. This section delves into these challenges, highlighting the complexities of developing accurate, ethical, and adaptable models

(1) Data Heterogeneity: Student data can be collected from various sources (e.g., academic records, surveys, behavioral data, demographic information), each with different formats and structures. Integrating these heterogeneous data sources into a unified model is a complex and challenging task.

(2) Data Quality and Availability: Student datasets often have missing values due to data collection errors. Handling missing or noisy data while maintaining model accuracy is a significant challenge.

(3) Changes Over Time: Students' performance and behavior can evolve over time. Accounting for these changes presents a significant challenge in student classification.

(4) Scalability: As the volume of student data grows, models need to handle increasingly large datasets efficiently. Consequently, scalability and real-time application can be significant challenges, especially when using complex algorithms or deep learning models.

(5) Real-Time Decision/Application: In real-world applications, such as early intervention systems for at-risk students, there is a need for models to operate in real-time, requiring low-latency prediction capabilities.

(6) Student Diversity and Complex Behaviors: Students come from diverse backgrounds, and their academic performance is influenced by numerous factors (e.g., socio-economic status, mental health, extracurricular involvement). Capturing this complexity within a model without oversimplifying is a key challenge.

(7) Class Imbalance: In many educational settings, the distribution of students across performance levels or categories (e.g., high achievers vs. underperformers) is often imbalanced. This imbalance can result in biased model predictions and hinder the model's ability to generalize effectively.

(8) Dynamic Learning Environments: Different academic disciplines and institutional contexts may require different classification strategies, and adapting models to a wide range of higher education environments can be difficult.

(9) Generalization Across Institutions: Models that work well in one educational setting may not generalize to another due to differences in institutional policies, curriculum, or student characteristics.

(10) Model Interpretability: Many ML models, especially deep learning approaches, are often seen as "black boxes," making it difficult to interpret their decision-making processes. Educators and administrators need clear, understandable results to make effective decisions.

(11) Evaluation Metrics: A key challenge in assessing student profiling or classification models in education is identifying an efficient metric that truly reflects the complexities of student outcomes. Traditional metrics, such as accuracy, often fail to capture the nuances of educational contexts, where success is not solely defined by exam scores or graduation rates. For example, a model might classify students effectively in terms of performance but overlook other important factors like engagement, motivation, or individual learning barriers. Moreover, metrics need to consider fairness, ensuring that predictions do not disproportionately favor or disadvantage certain groups, and interpretability, so educators can understand and use the results to make informed decisions. Developing a

comprehensive and efficient metric that balances these multiple dimensions while aligning with the diverse goals of education is a significant challenge for researchers and practitioners in the field.

(12) Data Privacy and Security: Ensuring student privacy while using personal or academic data is crucial. Striking a balance between leveraging data for effective classification and adhering to legal/privacy constraints remains a challenge.

9. FUTURE DIRECTIONS

While significant progress has been made in the field of student classification, there remain several areas where future research can contribute to enhancing the accuracy, fairness, and applicability of these systems. As the landscape of education continues to evolve, it is crucial to address existing challenges and explore new opportunities that can lead to more effective and inclusive student assessment methods. In this section, we outline key directions for future work that could help advance student classification models and improve educational outcomes through better data-driven insights and interventions.

(1) Integration of Psychiatric and Educational Expertise: Future student classification models could benefit significantly from integrating psychiatric and educational expertise. Collaborating with mental health professionals and educators can lead to more holistic models that better account for emotional, cognitive, and behavioural factors influencing student performance. This interdisciplinary approach could enable early identification of at-risk students, offering more tailored interventions that address both academic and psychological needs.

(2) Improved Methodological Transparency: To ensure robustness and replicability, future research should focus on improving the transparency of methodologies used in student classification studies. Providing detailed descriptions of data collection, preprocessing steps, and validation procedures will increase the credibility of research findings and make it easier to compare results across different studies. Additionally, adopting more advanced ML techniques such as ensemble methods or unsupervised learning could enhance the accuracy and depth of the models being developed.

(3) Real-Time and Adaptive Classification Models: The development of real-time and adaptive student classifi- cation systems is critical for applications such as early intervention. Future research should focus on creating models that can process data in real-time, offering instant feedback to educators and enabling timely support for students. Enhancing the scalability of these models to handle large volumes of data and reducing latency for low-latency predictions will ensure their practical application in diverse educational environments.

(4) Advanced Handling of Data Heterogeneity : Student data is often heterogeneous, coming from diverse sources such as academic records, surveys, and behavioral tracking systems. Future work should explore advanced ML techniques, such as transfer learning and multi-modal learning, that can effectively integrate these diverse data sources while maintaining the integrity of each. By improving how heterogeneous data is handled, models will be able to provide more comprehensive and accurate insights into student behavior and performance.

(5) Continuous Model Learning: Rather than training models once and deploying them, future research could explore the use of continuous learning or online learning models that can adapt over time as new student data becomes available. This would ensure that the models remain up to date and relevant.

(6) Longitudinal and Temporal Analysis: Students' academic trajectories and behaviors evolve over time, making longitudinal and temporal analysis essential for accurate classification. Future research should focus on developing models that track students over extended periods, capturing changes in their performance and behavior. These models can help identify patterns of decline or improvement, allowing for more timely and personalized interventions that reflect the dynamic nature of learning.

(7) Context-Aware Models for Diverse Educational Settings : Different educational institutions and disciplines require tailored classification strategies. Future work should focus on developing context-aware models that adapt to varying curricula, pedagogies, and institutional policies. This adaptability will ensure that student classification systems are relevant and effective in a wide range of academic environments, from traditional

universities to online learning platforms.

(8) Explainable and Interpretable Models: Future research should prioritize developing explainable AI tech- niques that make the decision-making processes of classification models more transparent. By providing clear, understandable results, these models will increase trust and allow educators to make informed, data-driven decisions.

(9) Data Privacy and Ethical Considerations: Protecting student data is a paramount concern in the development of classification systems. Future research should explore privacy-preserving techniques, such as federated learning or differential privacy, which allow for effective analysis without compromising student confidentiality. Additionally, ethical guidelines must be established to ensure that student data is used responsibly, balancing the benefits of data-driven insights with the need for privacy and security.

(10) Cross-Institutional Collaboration and Benchmarking: To improve the generalizability of student classifica- tion models, future research should encourage cross-institutional collaborations. By pooling data and knowledge from various educational settings, researchers can benchmark models against diverse student populations, ensuring their applicability across different contexts. Collaborative efforts will also help identify best practices and create a more standardized approach to student classification research.

10. CONCLUSION

This paper has reviewed different models and approaches for student classification in higher education, highlighting their strengths, limitations, and the challenges associated with their implementation. It also outlines key directions for future research, emphasizing the development of more robust, ethical, and accurate methods for student classification in this context. Furthermore, as the educational landscape continues to evolve, it is crucial to explore the integration of emerging technologies, such as ML and AI, to improve prediction accuracy and personalization. In conclusion, fostering a more nuanced understanding of student needs and behaviors will contribute to creating more equitable and effective educational environments.

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