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Research Article

Artificial Intelligence for Assessment and Feedback to Enhance Student Success in Higher Education

Monika Hooda [ID],[1] **Chhavi Rana** [ID],[1] **Omdev Dahiya** [ID],[2] **Ali Rizwan** [ID],[3] **and Md Shamim Hossain** [ID][4]

[1]*Department of Computer Science and Engineering, University Institute of Engineering and Technology, Maharshi Dayanand University, Rohtak, Haryana, India*
[2]*School of Computer Science and Engineering, Lovely Professional University, Punjab, Phagwara, India*
[3]*Department of Industrial Engineering, Faculty of Engineering, King Abdulaziz University, Jeddah 21589, Saudi Arabia*
[4]*Department of Marketing, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh*

Correspondence should be addressed to Md Shamim Hossain; shamim.mkt@hstu.ac.bd

The core focus of this review is to show how immediate and valid feedback, qualitative assessment influence enhances students learning in a higher education environment. With the rising trend of online education especially in this COVID-19 pandemic, the role of assessment and feedback also changes. Earlier the assessment part is not considered the main focus in learning and teaching in HEIs, but now with the increase in online education, it is observed that the paradigm is shifted toward assessing those activities of students that enhance their learning outcomes. A lot of research work has been done on developing assessment strategies and techniques that can support learning and teaching effectively. Yet, there is limited research that looks at how methods applied in learning analytics can be used and possibly constitutes the assessment process. The objective of this work is to provide an exploratory and comparative study of how assessment and feedback practices can enhance students learning outcomes using AI. The key contribution of this study attempts to capture an outline of the most used artificial intelligence and machine learning algorithms for student success. The results showed that I-FCN performed better than other techniques (ANN, XG Boost, SVM, Random Forest, and Decision Trees) in all measured performance metrics. Also, the result of the comparative analysis study will help the educators, instructors, and administrators on how they could take the advantage of a data-driven approach, design less pressurized, more valid, reliable, constructive assessment findings, and connect the power of assessment and feedback to enhance the learning outcomes.

1. Introduction

Assessment initiated a continuous cycle of improvement and is the evidence of learning. Assessment and feedback are considered as important factors of focus in the higher education environment as it influences all kinds of stakeholders (students, instructors, administrators, etc.). Teachers spend a significant amount of time in the assessment and feedback process, but there is very little progress in how to strategize assessment, also on how to make reliable feedback, and to analyze the impact of both in higher education environment [1]. The role of assessment in higher education improves their grading capacity, motivation values, performance, and advancing learning [2, 3]. Advancements in electronic technologies and information science are ushering us into a technological world in which computers are progressively being invented and formulated to meet human requirements while becoming smarter [4, 5]. Many researchers have emphasized the importance and impact of assessment on students learning in higher education. Recently, the role of assessment and feedback is widened as it is not only students-centered but also covers curriculum design, teachers' instructions, and administrators' settings. Assessment helps in improving the performance of students learning and acts

as a key factor in their future attainment [2]. There is widespread agreement that Artificial Intelligence (AI) will become one of the most useful technologies in the next years, alongside robots, virtual worlds, 3D printing, and Internet [6, 7]. Many frameworks for assessment for enhancing students learning outcomes are also proposed [8, 9].

Artificial intelligence attempts to simulate the natural intelligence of human into machines. AI systems can learn from past experiences or outcomes and make decision on the basis of these experiences. The applications of AI are growing in every field such as agriculture, industries, medical, and education. Machine learning is a subsystem of artificial intelligence. Machine learning algorithms helps the instructors in systematic monitoring of student's performance in the course and can take preventive measures to support struggling students. From researches it is observed that AI helps HEIs to improve quality of education by improving students' final outcomes.

Assessment can take multiple forms conferring to the purpose of assessment within the learning environment in the course. It could be diagnostic, formative, summative, or e-assessment. Some other types of assessment tasks are also seen and used within higher education: self-assessment and peer assessment. Choosing the right type of assessment type depends on the need and what kind of learning outcomes is needed during the course. Formative assessment "assessment for learning" can be performed throughout the learning process, whereas summative assessment, that is, "assessment of learning" is frequently performed at the end of all learning activities [10]. AI is applied in a range of scenarios, such as smart buildings and transport systems, smart transportation, health, compete effectively (called the "fourth industrial revolution" by some writers), and smart education, sometimes known as "learning aids" [11, 12]. Formative assessment (i.e., provide immediate and meaningful feedback to students about the learning outcomes at the end of the course contents) approaches and skills are superior to meet HEIs needs—to improve teaching levels of teachers which in turn improvise students learning outcomes and raise their achievement level [13]. Positive effects are seen of peer assessment on students learning autonomy (i.e., self-skills development, and self-motivation) [14, 15]. After introducing self-assessment in the learning process, an increase in student's pass rate can considerably impact student's overall performance [16].

In regards to ethical AI applications, UNESCO is developing a global platform to oversee AI uses and applications to guarantee that these new technologies are utilized responsibly. In order to defend principle of equality, we must examine the countless advantages while also expecting risks, harmful applications, and divides [17, 18]. The COVID-19 pandemic highly disrupted the higher education sector and shifted the old, chalk-talk teaching-learning model to an online learning format. This meant that the structure and nature of teaching, learning, assessment, and feedback methodologies also changes. Now, the assessment feature becomes more useful, powerful with the changing assessment parameters in order to enhance students learning outcomes in a digital learning environment [19, 20].

One of its most essential applications of AI is in education. We are talking for not only face-to-face teaching and smart online learning, but then also and perhaps most relevantly, e-learning, which enables direct and customized learning processes based on dynamic learning, computer vision, ontologies, conceptual systems, computational linguistics, and deep learning. There are many research works performed in the field of assessment and feedback, especially in the higher education sector [21, 22]. However, to the best of found experience, very few research works perform a study both of the theoretical discussion and practical implications of technologies in this area. Enough work has been done on developing assessment strategies and techniques that can support learning and teaching effectively. Yet, there is limited research that looks at how methods applied in learning analytics can be used and possibly constitutes the assessment process. The main goal of this survey is to provide theoretical and practical practices that help in a better understanding of assessment and feedback practices applicable in improving students' outcomes in higher education.

We address the following research questions in the study:

Q.1. What is the purpose of assessment and feedback?

Q.2. How does LA inform assessment as learning unfolds?

Q.3. What are the effects of assessment and feedback practices on student's performance, motivation, engagement, self-regulation, pedagogy, and curriculum/course design process?

This study aims to answer the above-stated research questions. Moreover, we designed a theoretical framework on assessment analytics and feedback to enhance students' outcomes in HE and also comparative performance analysis of various algorithms is performed and drafted in the paper accordingly and designed the figures and conclusion accordingly.

The structure of this review is as follows: Section 2 outlines assessment and its types in the field of higher education. Section 3 is dedicated to the purpose of assessment in HE. Section 4 presents a short review of the feedback concept. Section 5 presents the proposed theoretical framework on assessment analytics and feedback to enhance students' outcomes in HE on the basis of various theoretical and practical researches reviewed. Further in Section 6, a discussion on how can learning analytics inform assessment as learning unfolds is presented. Section 7 attempted to present the impact on assessment and feedback on domain-specific areas to enhance students learning outcomes. Section 8 shows the comparative performance analysis of various artificial intelligence, machine learning, and learning analytics algorithms that carry out implementation for assessing and proving quality feedback to stakeholders in HE.

Some of them are as follows:

(i) How students perform in a course?

(ii) Student engagement and progression level in a course.

(iii) Student motivation values.

(iv) Curriculum/course design.

Finally, the conclusion, limitations, and future work are revealed.

1.1. Problem Formulation. During the last two decades, the paradigm of e-learning has shifted. The use of the Internet for education has grown in popularity. Two crucial requirements for the accomplishment of today's modern virtual classrooms are continuous supervision as well as evaluation of material with learner-centered training and certification. Offline courses need to be assessed in such a manner that could help the learner in identifying potentially weak areas and ways of improving. Formative assessment involves modifying the models of teaching, training, as well as evaluation to modify academic achievement. Learning analytics is defined as the "analysis and examination of information generated through or acquired on students based to evaluate learning achievement, estimate future achievement, and uncover possible concerns," according to academics.

So far, no measures for student quality have been explored, as well as the opinions of all participants, including organizations, teachers, as well as learners, and also academic staff performance objectives, have been widely overlooked. This research will benefit the growth of the HE system by attempting to bring in a relevant collective tool as well as recommendations to decision-makers that will increase the performance of HEIs, as the sustainable strategy massive change due to private enterprise and global competition of learning.

Higher learning evaluation has generally concentrated on effective learning as well as implementation in confined situations, as evaluated by pen-and-paper examinations or academics projects like composing academic papers.

Assessment in higher education has traditionally focused on retention of knowledge and its application in limited contexts as measured by paper-and-pencil tests and academic assignments such as writing term papers. The growing volume of data produced in virtual learning environments presents both potential to learn statistics as well as issues relating to compatibility, confidentiality, as well as pedagogy, and institutional paradigms. As a result, new approaches as well as technology platforms are required to evaluate and interpret such statistics and to deliver personalized programs and assistance to users such as learners, academic staff, executives, as well as guardians. Taking insights and perspectives of the customized frameworks as well as designed to help effective teaching and learning process, cognitive and administrative paradigms also must be implemented. Furthermore, accessibility to information from various sources presents numerous concerns about privacy collaboration as well as scalability, and also confidentiality as well as institutional business associations.

There is limited research that looks at how methods applied in AI and LA can be used and possibly constitute the assessment process. The main goal of this survey is to provide theoretical and practical practices that help in a better understanding of assessment and feedback practices applicable in improving students' outcomes in higher education. Moreover, one of the goals of this study is to motivate the use of various AI and LA techniques to help HEIs. A novel assessment analytics framework is also designed that highlights the main focus areas that can be used to support quality higher education. So far no measures for student quality have been explored which is overcome by this research. Further, it is noted earlier, if the teaching process is limited and controlled, student assessment quality will also be limited. So teachers need a strong and persuasive strategy to set up learning situations and respond to student learning needs. All assessment types require greater transparency in all forms of teaching and learning and are also entirely iterative. The approaches provided in this work are ideal for researchers who are interested to explore the route of teaching and learning in a normal classroom and online classroom settings.

1.2. Expected Contribution of Research. Assessment methods are used by teacher's instruction that provides feedback to students to adjust ongoing teaching and learning to improve their achievement of intended instructional outcomes. The improvement of OL (Online Learning) in advanced education requires HEIs to move their intelligent and practices as far as learning viability. The asynchronously OL courses give open doors to an understudy focused way to deal with learning and assessment process. The web-based learning climate gives a platform to more execution-based assessment through real time and timely feedback, open doors for individual practice, and assistance. This study not only monitors learning process but also provides corrective measures and adjusts teaching to improve student learning. Through real-time feedback, possibilities for effective practitioners, as well as instruction, the interactive learning context provides a framework for further achievement evaluation. This study not just helps instructors to track cognitive activity of students in real-time but also provides the opportunity to students to participate as well as adapt instruction to enhance their academic achievement.

Each time learners respond with respective institutions as well as university academia's online educational environments, individuals leave evidence. Learning analytics-assisted evaluation explains how certain patterns can be optimized to enhance learners, education, as well as an effective system.

Educators can use a cognitive analytics-based evaluation foundation for effective e-learning, and learners can use that to improve overall academic performance. This data could be used by professional educators to identify areas of improvement in virtual learning development. Instructors can use the findings to create effective offline and online initiatives. This paradigm can be used by academic researchers to determine information from the learning analytics

platform's numerous evaluations. Integrating various perspectives would aid throughout the professional development of teachers. One of the goals of the study is to motivate the use of various AI and LA.

Techniques to inform learning and teaching in HEIs. Past studies within the arena of AI and LA have assessed students and provided feedback to students without explaining the reasons behind the assessment process. Such explanations will help students and instructors to synchronize them in a data-driven approach. The main aim of this approach is to answer, "why assess" and "role of feedback" in increasing student's outcomes and quality education.

2. An Overview on Assessment and Its Types

Assessment is the process of gathering information and intervening in that information using some criteria in order to form a judgment. Both assessment and feedback are a crucial part of the educational process—and their interface with learning, teaching, and curriculum—has always remained a significant element for getting successful learning outcomes and improving student satisfaction. There are a lot of survey studies revolving around assessments which are about the nature of assessments, including summative assessment and the formative assessment and the impact on students learning performance, motivation, and provide high-quality learning [6, 23, 24]. It is also seen that there are numerous studies on peer, and self-assessment arrived at the conclusion that peer, and self-assessment promoted student success, their participation in course and skills [25–28]. However, there is very modest elaboration in how to design assessment practices and make reliable judgments. In higher education environments, there is diversity in students' bodies, therefore, demands an increased need for inclusive assessment practices for enhancing students learning outcomes. Some research work totally neglected the pedagogical and cognitive elements while designing curriculum and assessment. Student reviews report examinees dissatisfaction with assessment and feedback [29–31]. This study highlights the current research, mixed-method (i.e., theoretical and practical) view on quality assessment in HE as helpful in suggesting many strategies and activities for an effective assessment environment that aids all higher education stakeholders.

2.1. Summative Assessment.
In summative assessment, students are assessed at the end of the course module. It sums up both the learning and teaching process and helps the instructors in knowing what the students achieve throughout the learning process. Grades, projects, term papers, and standardized tests are mainly used to assess students' performance in the course. From the study reviewed benefits to this method are as follows: (1) support the instructor in avoiding errors; (2) increase their error correction performance; (3) it provides reliable data (e.g., grades and mid-term marks) that can be used for accountability purposes for all kinds of stakeholders (e.g.,

learners, teachers, and administrators) in higher education environment; and (4) helps in informing educational plan (e.g., curriculum or funding departments) [32–34].

Traditionally researchers and HEIs focus on summative assessment to measure the students learning outcomes after a particular period of time without taking into account other features of the learning process, and the judgments provided to the students will not necessarily help them to improve learning. The introduction of learning management systems (LMS), massive open online courses (MOOCs), and other e-learning technologies makes summative assessment approaches hard to detect students learning activities and assess these activities [35–37].

2.2. Formative Assessment.
Formative assessment happens throughout the learning process. Formative assessment helps in students' learning process and enhances students learning outcomes [38, 39]. Various critical teachers' prerequisites—knowledge and skills, social factors, and psychological factors—for formative assessment are found useful for improving the quality of teaching and learning [40, 41]. Reference [13] develops a model of formative assessment enactment using the design-based approach of science teachers. The model is framed to analyze teacher's own FA practices, with the aim of getting better formative assessment strategies to achieve their purposes. Reference [42] presented a case study of STEM students where formative assessment strategy helps in decreasing dropout rates and hence improves student's performance. Results showed that there is a tremendous increase in students' performance after introducing the formative assessment strategy. Reference [43] designs a formative assessment tool for students where they improve their final grades by using automated feedback which helps both students and teachers in improving the learning process.

The benefits observed from the various surveys are as follows: (1) improves students' performance during learning, (2) promotes students' self-efficacy, (3) provides timely feedback, (4) minimizes students drop out rates by motivating them, (5) informs instruction provided by a teacher, that is, a key to structured pedagogy, and (6) helps in designing quality curriculum/course contents.

2.3. Self-Assessment.
Self-assessment is growing as a crucial learning and assessment strategy in the higher education sector to improve the quality of students learning as independent learners. Students can actively take part in their own evaluation process. Hence, the involvement of students in their own assessment process can increase their success rate [43, 44]. It is widely reported in many reviews and empirical studies that self-assessment can benefit academic achievement. It can be achieved through the activities such as self-grading and self-regulated learning [45, 46]. Several and similar studies [16, 47, 48], showed the connection between self-assessment and self-regulated learning. The findings of these studies clearly showed that there is a positive correlation between self-assessment, self-regulated learning (SRL), and self-efficacy strategies. However, there are a

significant number of studies giving proof that uncovers and reveals that self-assessment improves student's motivation, engagement, their outcomes in computer-based, mobile-based, pen-paper based, and e-learning-based education environment [49, 50].

2.4. Peer Assessment. Peer assessment has been gradually researched and discussed as it improves students' learning self-sufficiency and boosts their confidence in learning ability. A review of recent research [14] showed that the online form of peer assessment is more common, as it acts as an early intervention means by decreasing teacher's intrusion than the traditional form of peer assessment. Most of the peer assessment studies have been carried out to determine the validity and reliability issues of peer grades, that is, if the student's assigned grade is equivalent to teachers' grades [51, 52]. Further peer assessment frameworks such as PRAISE (Peer Review Assignments Increase Student Experience), Peer Scholar, Peerwise, are also discussed by their studies to give more support to the peer assessment process. Oral presentation, portfolios, articles, test performances, online discussions, quizzes, etc., are the most common products observed during the survey that are assessed using peer assessment approach [53, 54]. Mixed methods survey has been conducted which shows positive and significant relationship between teachers' assessment and peer assessment by using the scoring rubric to collect data for the study [24]. A recent study [55] presented a meta-analysis that studies the role of peer assessment in enhancing the academic performance of students and helps the instructor in optimizing the use of teacher's resources effectively. Numerous benefits are observed such as (1) making the range feedback wider and encourages students to reflect, (2) reduces marking load on teachers, and increases students' self-evaluation skills [17, 51], and (3) enhances students retention rate through motivation and reflection of their own learning [56].

3. Purpose of Assessment

Why assess? This question deals not only with the purposes of assessment but also issues related to assessment while supporting student success in higher education. This section is attempted to look for answers to this question by exploring the variety of researches and case studies. By exploring [57–64], it is found that the main purpose of assessment is as follows:

    (i) Motivation of students

    (ii) Feedback to students

    (iii) Feedback to teachers

    (iv) Measure students' performance

    (v) Measure students' progress in the course

    (vi) Curriculum/Course design

    (vii) Diagnosis

    (viii) Support student's collaboration

For long it is considered that "feedback on learning" is the main purpose of assessment; what about observing assessment also as "feedback on teaching"? Instead of "examination," the attention should be shifted toward "examining," consistent action of assessing learner's dialog, intelligence, and performance to inform teacher knowledge, methods, and skills that help learners during the classroom practice.

The issue the entire world is facing today is the COVID-19 pandemic, which transforms educational teaching and learning into online platforms. The higher educational settings are shifting from traditional methods of examinations to online assessment and feedback means that both the instructor and the learners have to uproot themselves to new means, formats, and contents of assessment and feedback. Some of the reviews are explored with methodologies including qualitative, quantitative, and mixed-method approaches regarding new assessment and feedback practices in the current situation [19, 59, 65].

It is also observed that "content is the best motivator," that is, if a curriculum/course is designed to actively engage learners through a variety of exploratory and analytical methods, it would make the process of learning interactive and more effective toward students' success. Curriculum and assessment work together cyclically and recursively to deliver learners and instructors with direction and focus [66].

The key purposes of assessment in the higher education section are categorized in Figure 1. This section contributes to the advancement to the future of researches as well as to the current growing work of articles on assessment in higher education.

4. Feedback and Its Purposes

Feedback is an essential part of the learning and teaching process as it helps students to identify gaps, self-assess, and act upon the provided insights, and inform instructors about the effectiveness of their teaching strategies and how to adjust these strategies according to student's needs. After the assessment process, feedback is provided to the higher education stakeholders to provide insights into students' performance as well as their strengths and fragilities [67, 68]. From the reviewed articles and research papers, it is observed that most of the papers focus on the instructor to students' feedback, but there are also some pieces of literature that focus on peer-to-student feedback. Currently, with the online learning environment, automated feedback is becoming an emerging focus area of research. Most effective and frequently observed feedback practices are teacher feedback, self-feedback, peer feedback, automated/computer-based feedback, and feedback modes are oral, written, e-mail, audio, video, rubrics, and web-based. Despite such huge literature, feedback is poorly implied and enacted by instructors and learners [67, 69]. The appropriate best feedback is assured to be wasted if students do not use it and implement it to enhance their performance actions. It is observed that it is not that students are receiving poor or no feedback, but they do not engage or recognize feedback provided to them, regardless of its quality. An active student
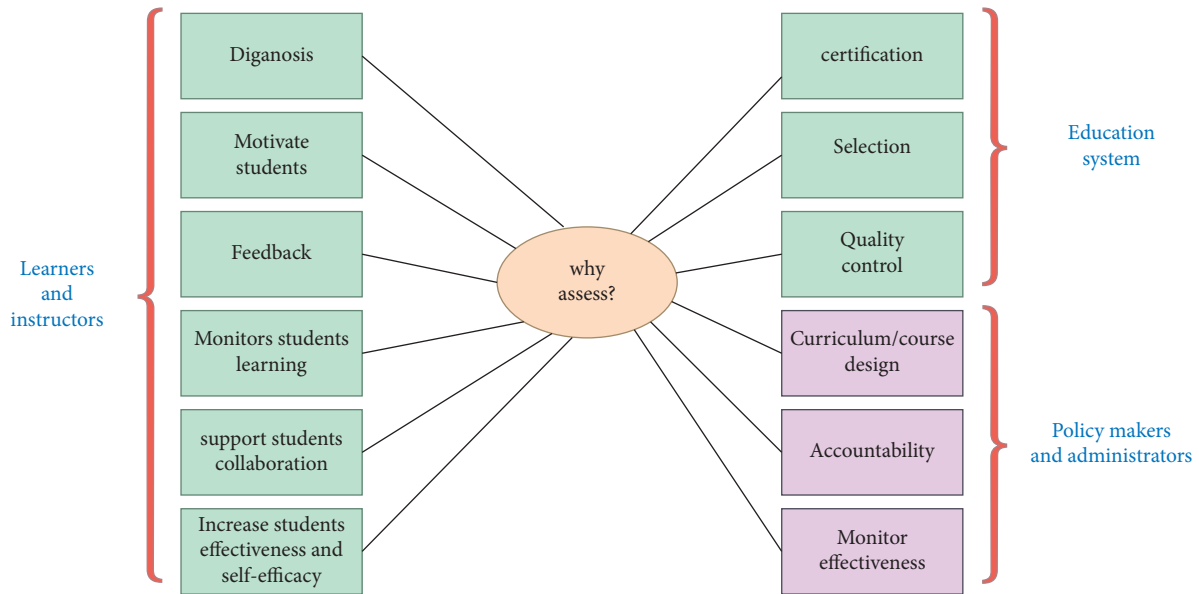
FIGURE 1: Purposes of assessment in higher education.

engagement with the feedback is necessary to support an effective learning process. Also, Rossiter [70] put emphasis on the fact that students need to look and recognize feedback when it is available to improve learning.

Also, there is a little review on the type of feedback and what type of feedback is best for what perspective in HE. Studies show that the features of quality feedback in higher education are important for all stakeholders. Feedback quality indicators are used by stakeholders in HE to encourage active student participation [71, 72]. In studies, it is seen that effective peer feedback enhances self-efficacy, metacognition, and academic achievement in HE. References [73–75] discuss the effect of web-based peer feedback. The findings show that effective peer feedback enhances academic self-concept (ASC). Reference [76] discusses types of feedback, techniques used to provide quality feedback, how adaptable the feedback is, and the quality and effectiveness of the feedback obtained. Findings showed that mostly automated feedback for programming exercises has been used to identify mistakes rather than fixing them.

Reference [77] adopted a socioecological approach for understanding feedback practices. Their findings show that time, scalability, and individual attitudes of staff and students are the major challenges while providing feedback. The concept of feedback loops is discussed which shows a trajectory of how students engage themselves in the feedback process, reflect and make ongoing adjustments during their learning process to enhance learning strategies [78].

Overall, the main reasons why effective feedback practices are necessary are the following:

(i) Enables self-regulation of learning

(ii) Increases student's motivation

(iii) Increase students' academic performance

(iv) Enhances student's engagement in the course which is a highly responsible factor in course completion rates

(v) Addresses accountability issues

(vi) Provides valuable information to teachers so that they can improve feedback practices, tasks, skills, and assessment.

This section concluded with the indication that with the current nature of educational research, there is a crucial demand for research to inform instructors, learners, HEIs the impact of feedback, and its purposes during the learning process because the old theory of feedback as the transmission of comments is being replaced in current pieces of literature by new theories which encourage better collaboration and dialogue between tutors and learners.

5. Assessment and Feedback Framework for Enhancing Students Learning Outcomes

Over the years, various frameworks are proposed for learning analytics. An early framework suggested by [79] considers six dimensions of a LA: (1) stakeholders, (2) internal limitations (required competencies), (3) external limitations (conventions, norms, and time scale), (4) instruments, (5) data, and (6) objectives. Also, the Learning process [80, 81], for LA contains five main components: (1) ability, (2) data, (3) culture and process, (4) governance and infrastructure, and (5) overall readiness perception. Moreover, other frameworks proposed for LA are the LALA framework consisting of four dimensions: (1) institutional, (2) technological, (3) ethical, and (4) community [82], Rapid Outcome Mapping Approach (ROMA) [83], the SHEILA Framework [84]. These frameworks help HEIs to identify their strengths and weaknesses to enhance quality education.
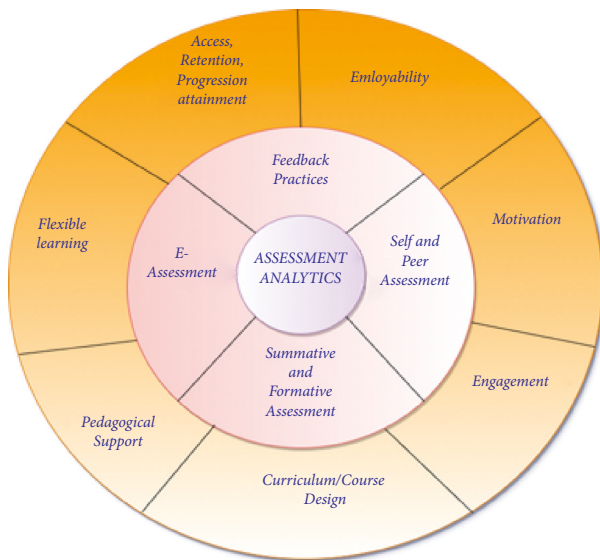
FIGURE 2: Assessment analytics and feedback framework for enhancing students learning outcomes based on the literature reviewed.

After reviewing the various presented frameworks for LA (Learning Analytics), finally a learning and assessment framework is designed. The proposed theoretical framework is motivated by the potential and opportunities that different types of assessment and feedback offered in an educational environment to enhance learning outcomes (see Figure 2). However, security and issues that occur during the assessment process are still missing in the proposed theoretical framework.

5.1. Who Is the Framework for? The framework is designed for all types of stakeholders in the higher education environment including teachers, students, HE administrators like the dean's head of departments, presidents, institutions, and policymakers.

5.2. Areas of Focus. The proposed theoretical framework highlights the four main focus areas from the findings that can be used to support quality higher education.

5.2.1. Summative and Formative Assessment. The balance of formative and summative assessment at the program level with formative assessment systematically implemented during learning and teaching can have a positive impact on students learning as well as improve the quality of academic standards. New methods and a variety of formative and summative can promote students' success (i.e., use technology-enhanced learning and innovative assessment methods).

5.2.2. Self and Peer Assessment. Opportunities for self and peer assessment within the learning and teaching environment enhance student's and teacher's understanding and trust in assessment strategies. Self and peer assessment

develops students as an independent learner and prepares self-regulation and employability skills in them and support collaborative learning concept.

5.2.3. E-Assessment. E-Assessment (or online assessment, CBA (Computer-Based Assessment), CAA (Computer-Assisted Assessment), and TEA (Technology-Enhanced Assessment) uses information technology in the different assessment process. It provides pedagogical support, grows practical skills, increases retention rate, and provides a flexible learning environment to learners by using e-assessment methods (i.e., rubrics, portfolios, social and collaborative assessment are the most common methods observed during findings). This is the reason why e-assessment is the main focus area of learning analytics research.

5.2.4. Feedback Practices. Feedback is a crucial component for helping students to attain desired learning outcomes. It is important not only for knowledge acquisition but also for learner motivation and satisfaction. With the empowerment in technology, timely and effective feedback is provided by teachers to achieve greater learning. Through the studies, it is noted that negative feedback discourages the effort and achievement of learners, so it should be carefully crafted and delivered. A set of principles (i.e., timely, transparent, ongoing and consistent, constructive, and meaningful) for effective feedback can be valuable for learning and teaching.

5.3. Impacts. Assessment analytics and feedback framework have individually and collectively had an impact upon student success in higher education by influencing the following:

(i) Quality of learning: the knowledge, skills, and problem-solving capacities of an individual in higher education

(ii) Quality of teaching: the quality design, delivery of teaching, use of technology-enhanced techniques for teaching as essential to the enrichment of any discipline

(iii) Curriculum design: the outline, design, content, interactive activities, and delivery of the curriculum

(iv) Pedagogy: the most effective methods of content delivery according to the needs of learners

(v) Engagement level of students: the degree of attention, interest, passion, and progress in the course

(vi) Motivation: the reinforcement to achieve high performance and success in the course

(vii) Student retention and progression: the academic success of students or completion rate of a course and students who progress from one academic level to the next level

5.4. How This Framework Can Be Used? This framework can discuss the four main focus points and the various impacts of

assessment and feedback in the wheel design provide a structure to shape assessment and feedback practices at the institutional level, department level, and individual level in the higher education system. It can be used to inform higher education institutions to develop strong assessment and feedback strategies and practices for student success and curriculum improvement.

6. How Learning Analytics (LA) Inform Assessment as Learning Unfolds

This section collects and summarizes the shreds of evidence on the usage of LA to inform the assessment process (see Table 1). It is tried to identify how learning analytics helps HEIs in the assessment process while learning is going on. Empirical research and case studies are gathered, and the main aspects of these studies are classified including their focus, data collection methods, approaches, and key outcomes [96, 97].

The existing methods of LA and EDM with a problem statement, performance metrics, and future scope are depicted in Table 2.

The results of recent studies showed that learning analytics can provide an accurate understanding of the learning process. The results illustrate the usage and implementation of learning analytics in the assessment process. Learning analytics helps institutions during formative, summative, peer, and self-assessment processes by utilizing available data efficiently and effectively in decision-making, can simplify the assessment of the usefulness of pedagogies and instructional designs for upgrading, and assist to monitor carefully students' learning process and purpose, detect undesirable learning behaviors and emotional states and monitors students learning to provide ongoing to students.

The existing literature on learning analytics and assessment discussed in this section has focused mainly on the current year's researches, despite being increasingly adopted in the higher education field. The findings of this section support HEIs (both in online and distance educational process) to keep abreast of this emerging area and have a base for further exploration of EDM and LA field.

7. Impact of Assessment and Feedback on Students' Outcomes

Existing literature in higher education provides information on frameworks, case studies, researches, and ideas on assessment and feedback. In this section, a mixed-method approach is used to show the impact of assessment and feedback on student outcomes. Performance feature is related to students' effort, achievements, the amount and quality of education, skills, abilities, and outcomes during the learning process. The relationship between the assessment practices, feedback, and student performance has been explored in numerous researches and case studies with the results viewing higher performance and deeper learning. Recently, in [118], semantic-aware technique is proposed to provide personalized feedback to learners. The advantages of the proposed technique are that it is applicable to several real-world problems and is scalable in nature. It is also observed that the delivery mode of assessment also has a great impact on students' performance. Also, [119] investigated the outcomes of feedback on quality performance in math web-based practice tests. Results showed that immediate feedback gives better result in improving students' outcomes than the delayed feedback. Moreover, [120] showed that the students experienced greater academic improvement and a positive impact on their learning correlated with active learning pedagogy by implementing regression and Propensity Score Matching (PSM) techniques. Recently, [121] studies the "self-assessment" impact on student's performance via rubrics techniques. Results showed that the quality of students and learning performance are highly correlated.

Engagement is strongly related to teaching effectiveness and directly affects the students learning outcomes. From the research studies, it is noted that student's engagement in the course is directly correlated to course satisfaction and achievement of course learning objectives. Assessment and timely feedback are observed to be the key to unlocking student's engagement in the course. Reference [6] studies the impact of assessment on student's engagement in VLE (Virtual Learning Environment) using the "one-way analysis of variance" (ANOVA) method and by "Tukey's honestly significant difference" (HSD) posthoc test. The result shows that continuous e-assessment increases students' engagement during their learning process. Gamification is becoming a popular and innovative way to support both instructor and learner in the educational field with learning or behavioral challenges. Currently, [122, 123] studied gamified e-quiz exercises in a formative assessment context. In this study, four different types of learning engagement (behavioral, emotional, cognitive, and agentic) are discussed for performing the assessment. Spearman's nonparametric correlation is used by them to determine the associations between the gamified e-quizzes and paper-based quizzes scores. Cognitive engagement involves the internal thought processes involved in a student's course. Reference [124] discussed the usefulness and effectiveness of detailed feedback in the online CDA (Cognitive Diagnostic Assessment). Their research results showed that detailed feedback helps in enhancing student's achievement and engagement in the learning process. Reference [125] investigated the impact of assessment design on student's engagement, satisfaction, and passing rates in a course. Findings indicated that engagement, satisfaction, and pass rates of students in the learning environment are not just greatly influenced by learning design but are especially manipulated by how instructors stabilize their learning design activities in the course modules on weekly basis. Their study also supports visualizations to enhance the quantitative evaluation of these learning and assessment designs.

Motivation can be accomplished through appropriate assessment and feedback practices and conditions. There are numerous studies that showed the effect of assessment and feedback practices on student's motivation. The impact of different types of assessment and assessment modes on student's motivation are investigated. Studies

TABLE 1: Researches and case studies reviewed to summarize the use of learning analytics to inform assessment as learning unfolds.

S.no	Focus on the type of assessment	How data are collected	Methods/approaches applied	Key outcomes
1.	E-assessment [85].	E-learning environment	Rule-based fuzzy reasoner	Support personalized and adaptive learning environment, and support pedagogical approaches
2.	Automated assessment [86]	Academic marks of students in face-to-face learning (years 2013–2019) and online questionnaire in the academic year 2018–2019	Decision trees Naïve Bayes ANN SVM	Automated feedback increases the involvement of both instructors and students in the learning environment
3.	Computer-based assessment and feedback [87]	Collect data from the computer-based environment	Inductive data-grounded approach	Help teachers to improve their instruction
4	Formative assessment [88]	Learning management system	Data-driven approach	Provide actionable recommendations and support self-regulated learning
5	Assess collaborative learning [89]	Asynchronous online discussion	Design-based approach	Improves students' performance when monitored using learning analytics and reduction in the drop out is observed based on the feedback sent in classrooms
6	Formative assessment [90]	MOOC	Anomaly detection Method	Reduced cheating without negotiating learner's engagement in formative assessment
8.	Formative assessment [91]	Intelligent learning environment (ILE); wiki environment	Statistical analytic technique and item response models (IRT), i.e., RASCH model is used	Describe a web-based system (BASS) to purpose, increase, and deliver assessment and feedback; helps to diagnose students, instructional needs a cognitive ability
9.	E-assessment [92]	Big data environment; social networking sites such as Twitter Facebook, Google, and LinkedIn	MapReduce-based genetic algorithm MapReduce-based SNA (social networks analysis)	Improve the quality of the learning process
10.	Assess blending learning [93]	Collected data from different sources such as moodle, and personal spreadsheets	Visual learning analytics techniques (zar bar charts, line charts, radar charts, fiddle charts, or box-and-whisker plots)	Competence-based learning environment (COBLE): helps to detect students anomalies and deliver satisfactory feedback to resolve them; also monitors students and supports teacher reflection
11.	E-assessment [94]	MCQs and subjective types questions from an e-learning environment	NLP (natural language processing) techniques	Helps to identify learner's knowledge about the course and detects the cognitive ability of the learners
13.	Formative and summative assessment [33]	Data collected from R commands in the form of short comments	NLP (natural language processing)	Enhances both enactment, features, and quality of formative and summative assessment processes which further improve the learning outcomes
14.	Formative assessment and summative assessment [95]	Data form STEM disciplines (like MCQs, fill in the blanks) and VLE (like logs or databases)	DBR (design-based research) and MAB (multiarmed bandit) based algorithms	Learning design-analytic (LDA) model proposed to: mitigate the learning barriers such as learning consciousness, learning process tracing, educational intervention, and learning motivation

showed that self-assessment improves student motivation. Reference [49] presented a study that shows the impact of assessment on students' motivation and achievement during the learning process. It is observed that feedback is mainly discussed in the context of formative assessment, but now it is gradually considered in the light of self-regulated learning, self-assessment, and peer assessment. Reference [59] conducted research during COVID-19 lockdown and showed how students' motivation is extremely correlated with students' self-assessment. They design a self-assessment dashboard that displays a set of activities for students to be performed.

TABLE 2: Comparison of various existing techniques of LA/EDM.

Author's name	Methods name	Problem/gaps	Performance metrics	Future scope
Vaidya and Saini [98]	Conventional learning-based educational data mining and learning analytics	Implemented only on computer-based systems	—	Standard data management schema will be used for gathering the data
Ranjeeth et al. [99]	Association, clustering, statistical methods	Data gathering issues / Data security issues	Social waves / Statistics	Advance learning techniques will be implemented to resolve the data security issues
Xiao et al. [100]	Mobile learning-based system	Need to gather more diverse and objective data	—	Brain wave analytics will be implemented to handle diverse data
Distante et al. [101]	MILA learning analytics-based model	Limited to only some visualizations	—	Moodle VLE will be implemented for the improvement of learning and teaching process
Valenzuela et al. [102]	Thematic-based analysis approach	Inefficient volume of data	—	Eclectic methodology will be applied for learning enhancement
Javidi et al. [103]	Induction rule-based algorithm	Privacy and security issues	—	Inefficiency of data will be reduced
Costa et al. [104]	EDM and learning analytics	Risk of students data misuse	—	Framework will be enhanced to make real-time system
Jamila et al. [105]	Artificial neural network based learning analytic system	The network's duration is unclear	—	Deep learning-based methods will be implemented for efficient outcomes
Krikun [106]	Five-stage framework	To perform the classification of individuals who received additional course profiling is difficult to classify	—	Mumford and honey learning models will be used for better results
Surenthiran et al. [107]	Deep belief—neural network	Limited dataset / High computational time	Accuracy / Error rate	Optimization technique will be enhanced for efficient results
Hussain et al. [108]	Deep learning base regression analysis methodology	The network's duration is unclear	Accuracy	More data will be gathered for training of the model
Huang et al. [109]	ANN and SVM-based algorithm	Data argumentation issues	Accuracy / Precision / Recall	Multiple class classification will be implemented
Tsiakmaki et al. [110]	Fuzzy-based system	Poor results of feature extraction	Accuracy	Optimization technique will be implemented for further enhancement
Iatrellis et al. [111]	Two phase-based machine learning system	Limited dataset / High computational time	Recall / Precision / Accuracy	Clustering techniques will be implemented for further improvement
Bujang et al. [112]	Machine learning-based multiple class prediction	Low accuracy	F-measure	Over fitting issues will be resolved
Bhutto et al. [113]	Supervised learning-based algorithm	Need to extract hidden knowledge	F1-score / Precision / Recall / Accuracy	Hybrid features will be extracted for efficient results
Liu et al. [114]	Fusion attention based-deep knowledge system	Poor results of feature extraction	Accuracy / AUC / RMSE / MAE	Neural network will be enhanced for more efficient results
Song et al. [115]	SEPM (sequential engagement based academic performance model)	Low accuracy	Mean square error / F1 score / Recall accuracy	More demographic attributes will be extracted for more accurate outcomes
Fotso et al. [116]	Deep learning-based model	High computational time	Accuracy	More data will be collected for training of the model

TABLE 2: Continued.

Author's name	Methods name	Problem/gaps	Performance metrics	Future scope
Jain and Solanki [117]	Gradient-based extreme boosting classification	Need to use behavioral parameters	Precision Accuracy Recall Execution time F-measure	Optimization technique will be implemented for further enhancement

Currently, with the rapid evolution of online learning environments and social network sites, such as Facebook, Twitter, Instagram, and LinkedIn, students demand more independence or personalization in their personal learning environment and enhancing their pedagogical interactions led to more focus on assessment and feedback practices. Reference [126] explored the use of Facebook for peer assessment and the effect of peer feedback on students' learning process in the higher education context. It is concluded that students' motivational level is increasing, and they came to know about their strengths and weaknesses in their learning process. Online peer assessment assists students to correct their deficiencies and modify them according to the feedback provided.

Many types of research implied that students who are having strong SRL (Self-Regulated Learning) skills are more probable to be successful in e-learning or online learning [127]. Actually, SRL is dependent on self-assessment—via self-monitoring and self-evaluation—to assist the student during the learning process. Reference [47] explores the role of self-assessment in supporting Self-Regulated Learning (SRL) and self-efficacy. In their meta-analysis process, they included four variables that affect SRL and self-efficacy: gender, age, types of self-assessment practices, and the agent who implements the assessment (i.e., the instructor or the researcher). The results of their findings showed that self-assessment interventions have a direct and positive relationship with students' SRL strategies. In addition, formative assessment and feedback provide strong facts of improvement and stimulating students' reflections skills. Reference [128] discussed the impact of formative assessment on instructor's knowledge to support students' reflection skills. Also, a discussion on the role of quality feedback for improving the learning outcomes in the context of the self-regulated learning concept is done. Reference [129] discusses the role of good feedback practices in the learning process and how it enhances students' performance, provides opportunities to instructors to improve learning methodologies and removes students' course difficulties. Currently, researches that show positive associations between personalized feedback with students' learning strategies together with time management strategies—the most essential aspects of SRL, are becoming popular. In a recent study [130], personalized feedback messages are provided to students based on their engagement and performance on the formative assessments. The feedback offered to students helps them in evaluating their knowledge about their academic outcomes and advises them on how to upgrade on that result. The findings show that personalized feedback informs students about the gap between their current achieved performance and desired performance.

Assessment and feedback approaches help students and teachers to provide pedagogical benefits. Numerous recent studies aimed to pay attention and more focused on the concept of the role of assessment and feedback in improving pedagogy in the HE environment. Reference [90] develops and validates MOOC assessment models that support learner-centered pedagogy, without sacrificing the reliability of the assessment for certification. The findings of the study show positive results, support pedagogy, and motivate learning by decreasing the amount of cheating. Recently, the concept of competency-based assessment has experienced an essential development in the education field. Competency-based assessment act as a diagnostic, remediation, and improvement key to helping learners in improving their skills. Reference [131] proposed an innovative assessment approach by offering pedagogical situations to enhance and remove shortcomings in each learners' skills (such as reason, analyze, realize, validate, and communicate). Artificial intelligence technology is used in its approach to monitor the performance of each student during the entire learning process. Not only to students, but their intelligent system also helps and supports teachers in making better decisions. Moreover, Dietrich et al. [132] discuss different kinds of formative assessment methods for making improvements to pedagogical implements consisting of visualization features, and also, they examine the impact of the feedback practices on both the visualizations along with teaching exercise.

Curriculum/course design is of the key importance in the learning process. A clear and concise course design is fundamental to effective student learning. There are a variety of researches and case studies that showed designing a curriculum that focuses on enhancing student learning. In such an education crisis, do the instructors have enough and adequate skills to design, strategize, and deliver online instructions? So instructors have to take hold of new roles of designing course modules, tasks, assignments, content presentation, assessments timely feedback using various different tools. Recently, Looi et al. [133] provide a mixture of the roles of the teacher in online learning tasks. From their findings, it is observed that online learning provides openings as well as limitations for teachers from being deliverers of the educational curriculum to being designers of learning tasks, in addition, provides instructional designs for interactive technologies. The instructor has to select the high-quality, finest content of the curriculum/course that well matches the students' level of skill and knowledge. They also discuss some challenges and opportunities for the teacher's growth. A well-designed curriculum confirms proper academic and professional development. To improve higher education quality and more

TABLE 3: Researches and case studies showing the impact of assessment and feedback on student outcomes.

S.No	Authors	Impact on students' outcomes
1	Marin et al. [118]	Helps in increasing students' self-reflection
2	Attali and van der Kleij [119]	Students performed better with immediate and timely feedback provided to them during learning
3	Crimmins and Midkiff [120]	Improves students leaning pedagogy and final course grades
4	Vasileiadou and Karadimitriou [121]	After self-assessment student's performance increases
5	Holmes [6]	Increases student's engagement with the course modules; helps in curriculum design effectively
6	Zainuddin et al. [122]	Increases student's pedagogy and engage students more in the course
7	Park et al. [123]	Supports collaborative learning; helps in improving socioemotional engagement during learning process
8	Chin et al. [124]	Detailed feedback enhances student's achievement
9	Nguyen et al. [125]	Assessment enhances students' engagement, satisfaction,, and decreases dropout rate
10	Nikou and Economides [49]	Positive effect is observed on students learning motivation and achievement
11	Papamitsiou et al. [59]	Support learner's motivation and interest in learning, support self-regulated learning
12	Demir [126]	Promotes students' interest in learning process; improves learner performance and self-reliance
13	Broadbent [127]	Supports self-regulated learning which directly increases students' academic grades
14	Panadero et al. [47]	Promotes students' use of learning strategies; supports self-motivation and self-efficacy
15	Tigelaar and Sins [128]	Support students' reflection skills; help the teachers in intending quality feedback
16	Ott et al. [129]	Feedback interventions guides students during their learning process and improves their learning outcomes
17	Lim et al. [130]	Promotes students self-regulated learning; promotes students effective engagement
18	Alexandron et al. [90]	Supports learner-centered pedagogy; motivates students to engage more in the course
19	Diyer et al. [131]	Helps in-time management tactics during the course; helps instructors in promoting learning strategies for better outcomes during learning
20	Dietrich et al. [132]	Helps learners to upgrade their self-pedagogy; helps instructors in refining instructional strategies and course contents
21	Looi et al. [133]	Supports student's motivation, relationships, and their well-being; promotes instructors' skills in delivering instruction; helps in modifying curriculum and course designing
22	Islam [134]	Helps in designing curriculum to support high-quality education
23	Yan and Lin [95]	Scales up personalized and adaptive learning; improves absence of self-awareness of learning

employment graduates, designing and implementing a good curriculum is desirable. Reference [134] examines several aspects of the curriculum by using the feedback data from stakeholders. They analyze the stakeholders' responses on assessment need, curriculum design, curriculum assessment process, curriculum arrangement, curriculum gaps, the satisfaction of organizations' expectancies, and remarks of the stakeholders on the curriculum improvement plan. From their examination, a strong connection is achieved between curriculum and educational quality improvement. Reference [95] designs a "Learning Design-Analytic" (LDA) model that helps in recommending strategies to online educators for course designing. Thus, by implementing formative assessment, in-time and immediate feedback to struggling students they detect anomalies in the learning contents of the course.

Summary of researches and case studies that shows the impact of assessment and feedback on student outcomes are in Table 3.

8. Comparative Performance Analysis

The comparative analysis of various artificial intelligence, machine learning, and learning analytics techniques for assessing and providing quality and intelligent feedback to learners is discussed in this section using accuracy rate, precision, recall rate, and F1-score as performance metrics. For comparative analysis Improved Fully Connected
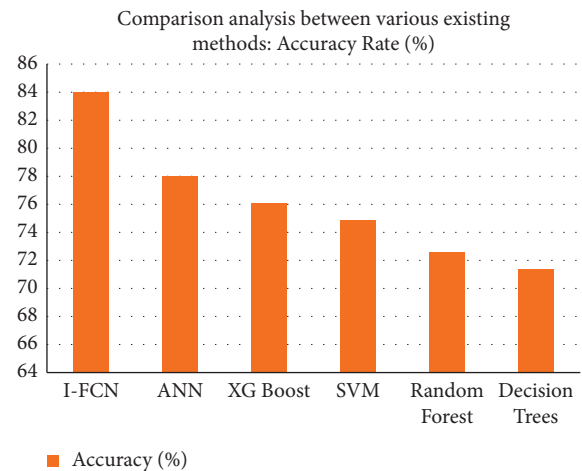

FIGURE 3: Accuracy rate of I-FCN and existing techniques.

Network (I-FCN) [135], Artificial Neural Network (ANN), XG Boost, Support Vector Machine (SVM), Random Forest, and Decision Trees are selected from the literature reviewed [136–138]. The comparative analysis is done using Open University Learning Analytics (OULAD) dataset. In this dataset, 32,592 students enrolled in 22 different module-presentations. It also contains students' academic record, their demographic record, assessment information, their
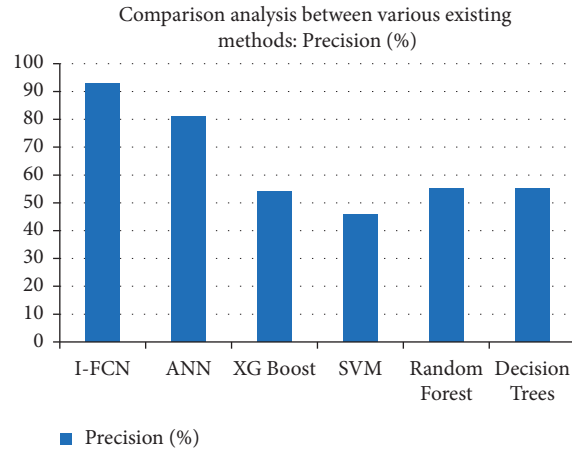
Comparison analysis between various existing
methods: Precision (%)

Figure 4: Precision of I-FCN and existing techniques.

Comparison analysis between various existing
methods: Recall rate (%)
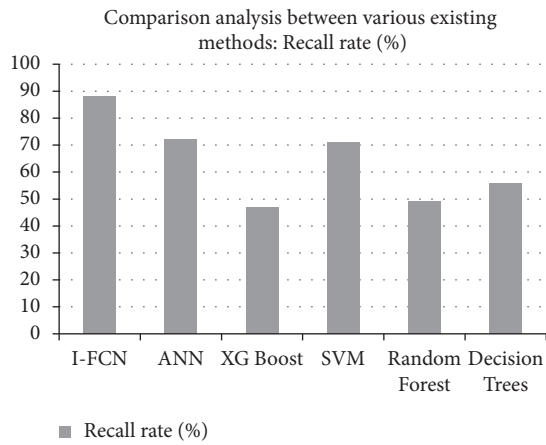
Figure 5: Recall rate of I-FCN and existing techniques.

Comparison analysis between various existing
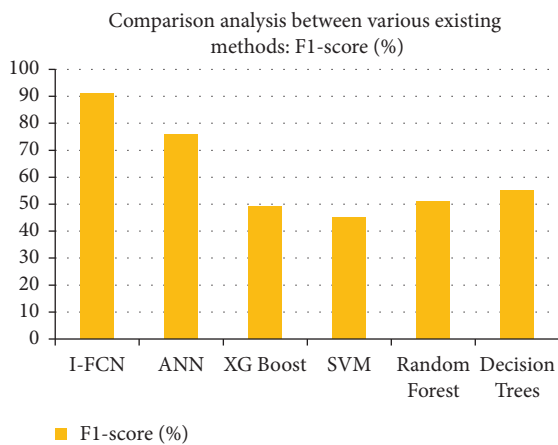methods: F1-score (%)

Figure 6: F1-score of I-FCN and existing techniques.

scores in the modules, and their interaction with Virtual Learning Environment (VLE). The dataset contains a set of seven tables (courses, studentInfo, student_registration, assessments, studentAssessments, vle, student_vle). The model run on python using Jupyter notebook.

It is observed from Figure 3 that I-FCN shows highest performance of 84%, followed by ANN with 78%. Decision tree has the worst performer in terms of accuracy rate, that is, 71.37%. Figure 4 depicts that I-FCN is most precise in assessing and providing feedback to students. The precision value of I-FCN is 0.93. Random forest and Decision have the least value of precision, that is, 0.55. Recall value of all the techniques is shown in Figure 5, and it is observed that I-FCN has highest value, that is, 0.88. Recall value for Random forest technique is least, that is, 0.49. F1-score recorded for I-FCN is 91% which is highest among all techniques, followed by ANN with 76% as shown in Figure 6.

9. Conclusion, Limitations, and Future Work

The current study aimed to explore the impact of assessment and feedback on students' outcomes and performance in the higher education system. We have found positive results of various assessment and feedback practices that can enhance the students' learning experience and outcomes. Furthermore, learning analytics will make it possible for higher education to support the learning environment, at different levels, for all the stakeholders with technical innovations and in the COVID-19 pandemic. The theoretical assessment analytics and feedback framework provided in this study has been a useful resource for all stakeholders in higher education and it is expected that this framework will provide something of value for future researchers. However, security and issues that occur during the assessment process are still missing in the proposed theoretical framework. The framework addresses seven strategic areas of priority, which Advance HE believes are key for change, is discussed. All seven are directed toward assessment analytics; at the center—for the achievement and enhancement of student success.

The analysis is performed on the OULAD dataset. The results showed that the best technique is I-FCN that outperforms many artificial intelligences, machine learning, and learning analytics techniques for assessing and providing quality and intelligent feedback to

learners. The results are demonstrated in terms of using accuracy rate, precision, recall rate, and F1-score. I-FCN shows highest performance at 84%, while decision tree has the worst performer, that is, 55% in terms of accuracy rate. Moreover, I-FCN is most precise, that is, 93% in assessing and providing feedback to students, whereas SVM is least precise with a value 46%. Recall value of I-FCN has highest value and worst for XGBoost technique. F1-score recorded for I-FCN is 91% which is highest among all techniques, followed by ANN with 76%, least value of F1-score recorded is for XGBoost.

It is hoped that the present study and the proposed framework will be useful for researchers and all higher education stakeholders, as assessment and quality feedback is the necessity of today's educational implication especially in the COVID-19 pandemic for productive learning.

The study is not exempted from the limitations. A little research-based development in how to design assessment and reliable feedback is discussed in the study. There is a needed to know more about how different methods are applied to carry out assessment and feedback practices. Features of assessment like validity and reliability are completely missing in the study to ensure students' achievement of the learning objectives. More research-based knowledge is needed to identify factors to create lifelong learning conditions for designing assessment practices and feedback processes. Specifically, based on the researches and case studies presented in this study, future research should study the impact of assessment and feedback practices on gender, culture, and age factors of students and the influence of these factors on lifelong learning. Moreover, the connection between students' cognitive skills (emotions, behavior) and the learning process: connections between positive emotions and improved learning, especially during online learning and teaching methods need to be explored further. This area of research can enlighten studies on the impact of various assessment methods on student cognitive skills such as emotions, motivation, self-awareness in OLC (Online Learning Community). A new technology AGI (Artificial General Intelligence) can be very powerful in the application of this area. Also, educational games and gamification techniques will be looking forward to enhancing and supporting lifelong learners beyond the walls of the classroom. Further, it is noted earlier, if the teaching process is limited and controlled, student assessment quality will also be limited. So teachers need a strong and persuasive strategy to setting up learning situations and responding to student learning needs. All assessment types require greater transparency in all forms of teaching and learning and are also entirely iterative. The approaches provided in this work are ideal for researchers who are interested to explore the route of teaching and learning in a normal classroom and online classroom settings. Researchers may also pull upon research to further construct the new and emerging technologies, for assessment and capturing students' feedback in online learning systems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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