




## Chapter 6

# Intelligent Frameworks for Assessment in AI-Enhanced Learning Environments


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### Introduction

Nowadays several critical challenges, opportunities, and trends in learning must be considered in the development and implementation of new learning environments. These include encouraging lifelong learning, valuing both informal and formal learning, addressing the open and social dimensions of learning, and recognising the different contexts where learning takes place. It is also crucial to address what today's students need. We observe, however, that during the last years, knowledge acquisition and learning have been distributed and continue to occur in a world without boundaries. Students are collaborating

more than ever beyond classroom boundaries, which become more and more irrelevant within formal settings. Moreover, the openness of knowledge resources and the social nature of the web through the participation, voting, collaboration, aggregation, and distribution it enables, are leading to a new generation of students, driven by openness, networking, and sharing. Considering the new requirements in terms of learning also raises challenges with regard to the assessment of learning. Student-centred and networked learning require new assessment models that address how to recognise and evaluate self-directed learning achievements.

We need to put the student at the centre of our focus and give them the control over the learning experience. We also need to help students to operate in decentralised and open environments, and provide them with different kinds of assessment according to their needs. Assessment is an integral part of instruction, as it determines whether the lesson's educational goals and standards are being met (Marshall, Zhang, Chen, Lally, Shen, Fox, & Cassel 2003). In the literature, researchers distinguish between different kinds of assessment. The main difference between the different concepts of assessment is the usage of data in the diverse assessment activities. When we consider the one kind of assessment, data are used to decide the direction for action in the learning process. In another kind of assessment, data are used to determine the extent to which an action was successful (Secolsky & Denison 2017).

Our research has specifically looked into assessment mechanisms. One way of increasing the efficiency of assessment is to allow students to assess themselves or each other. In addition, and within the continuously advancing domain of educational technology, the incorporation of AI (artificial intelligence) into the realm of assessment methodologies is increasingly recognised as a critical factor in enhancing and personalising educational experiences. ML (machine learning), a fundamental subdivision of AI, endows systems with the capability to autonomously learn from data. This function is essential for tailoring educational content and assessments within adaptive learning frameworks.

This chapter presents an overview of the specificities related to the deployment of technology-enhanced assessment, and the different forms of assessment that could be deployed using technologies. A special focus is on the semantic web which provides a framework for interoperability of data through various environments and possibilities for personalisation and adaptation for the students. The challenges related to the deployment of assessment in AI-supported learning environments are presented. In particular, we will focus on collaborative intelligent assessment, where we present a case study related to the deployment of our intelligent assessment framework and the results obtained.

## **Evolving Educational Challenges and Opportunities**

During the educational process, the dynamic character of the area of education is continually confronted with new obstacles and possibilities since education is not a static entity but rather an ever-changing environment influenced by many elements. This is evident from the research of Kayembe and Nel (2019) that social issues, inequality, and the marginalisation of socioeconomic groups are all representations of the difficulties that the educational system faces, whereas the opportunities that affect the educational systems are promoting innovation and creativity, partnerships and collaboration, and technology as a bridge for social inclusion.

Amidst this ongoing evolution, the educational sector faced an unprecedented hurdle in the form of the COVID-19 (Coronavirus disease of 2019) pandemic. Sadjadi (2023) explains the education system's challenges and opportunities during COVID-19, which are uncertainty in academic semesters, digital transformation of educational programmes, online education, capacity building, skill mismatch, and access to learning opportunities, whereas the opportunities that affect the educational systems are digitalisation, smart working, equality in digital access to education, long-term planning for capacity building, value creation, and relationship strengthening. From these opportunities, it becomes clear that the educational system can adapt, innovate, and create value in response to challenges

like the COVID-19 pandemic. Neuwirth, Jović, and Mukherji (2021) highlight some of the challenges that faced the educational systems during the COVID-19 pandemic: The transition to virtual classrooms, maintaining normalcy, psychosocial factors, diversities, and the inequitable distribution of resources. However, despite these challenges, they present opportunities for the educational system during and post COVID-19, such as unique learning opportunities, building resilience, and transferable skills.

Bonfield, Salter, Longmuir, Benson, and Adachi (2020) discuss the potentially disruptive technologies that present challenges and advantages to established pedagogies and course design. They also mention the need for IHEs (institutions of higher education) to redesign curricula to support lifelong learning, online learning, and developing skills for future employment. This underscores the importance of research and reflection to inform strategic conversations about the future role and importance of E4.0 (Education 4.0).

Moreover, that clears up the evolving educational challenges and opportunities, and explains the need for faculty and students to collaborate and adapt to the new virtual learning environment while also addressing the psychosocial factors and challenges.

### **The Rise of Open and Social Learning**

The current educational environment is experiencing a notable shift, characterised by the increasing prominence of open and social learning. Open and social learning approaches emerge as a critical factor as established educational paradigms undergo a major upheaval. The driving forces behind this paradigm change are technological breakthroughs, evolving student preferences, and a worldwide transition towards collaborative and inclusive learning experiences. The intersection of open educational resources, social media platforms, and collaborative online spaces signifies a shift away from conventional, exclusive educational approaches.

A study conducted by Hew and Cheung (2014) explores the rise of MOOCs (massive open online courses), a popular form of

open and social learning, and highlights challenges in teaching such as student reaction, fast feedback, assessment difficulties, and instructors who are facing challenges like time and resource demands. The opportunity to teach MOOCs includes the value of the diverse perspectives and resources generated by MOOCs, motivations like curiosity, and personal challenges faced by students and instructors. The rise of open and social learning, particularly through MOOCs, has therefore sparked significant interest and debate among educators, researchers, and students.

Veletsianos and Shepherdson (2016) discuss the rise of open and social learning in education. This includes the use of MOOCs, OERs (open educational resources), social media, collaborative and networked learning, inclusivity, and accessibility. The research explores the impact of open and social learning on equity, access, and participation in education, as well as the challenges and opportunities it presents for educational institutions, educators, and students. Issues such as quality assurance, accreditation, business models, and the evolving role of educators are addressed. The emergence of open and social learning reflects a shift in educational practices driven by technology and learner needs. Ongoing research continues to explore the implications and effectiveness of open and social learning in education.

The emergence of open and social learning therefore reflects a paradigmatic shift in educational practices brought about by technological advancement, shifting student needs, and the desire for more adaptable, inclusive, and collaborative learning experiences. Ongoing research and scholarly inquiry continue to explore the implications, effectiveness, and future directions of open and social learning in education.

### **The Need for New Assessment Models**

Academic literature emphasises the need for new assessment models that go beyond traditional academic knowledge. Scholars argue for assessing a wider range of skills and competencies, including psychological constructs like personality traits and EI (emotional intelligence). The increasing number of publications in this area shows a growing recognition of the importance of re-

evaluating assessment practices. The use of digital technologies has also sparked interest in more innovative approaches. There is therefore a commitment to developing more effective and comprehensive assessment models.

Wafubwa (2020) indicates that the assessment models have limitations in accurately measuring student learning and achievement, including limited scope, standardisation, reliability and validity, time constraints, pressure and stress, and bias. These limitations can negatively impact students' performance and the quality of their education. To address these issues, educators and policymakers should develop more inclusive, reliable, and valid assessment models that include multiple methods, accommodate diverse students, and ensure fairness and unbiasedness. Coiro (2021) points to the limitations of current assessment models in digital literacy and reading. It suggests a need for a more comprehensive approach that considers more than just comprehension. He emphasises the importance of the authentic assessment of comprehension and learning in complex digital spaces. Current models often focus on comparing reading on paper and digital screens, neglecting the complexities of readers engaging with diverse digital texts.

William (2011) explains why we need to shift to competency-based assessment, which is very important because current assessment models have flaws like putting too much emphasis on standardised tests, not being useful in the real world, not measuring non-cognitive skills well enough, and possibly being biased. This transition necessitates comprehensive, student-centred approaches and continual professional development for instructors. Nadelson, Heddy, Jones, Taasobshirazi, and Johnson (2018) mention that the use of multiple assessment methods, such as concept maps, exploratory factor analysis, confirmatory factor analysis, item response theory, and Rasch modelling, is crucial for a comprehensive understanding of conceptual change in science teaching and learning. This approach helps educators and researchers to gain a complete understanding of the factors influencing conceptual change, leading to more effective teaching strategies and interventions.

Due to the significant role of educators, it is crucial to enhance assessment without compromising its proficiency in utilising this technology during instruction and subsequent procedures. Opfer, Nehm, and Ha (2012) test developers have been urged to use an “assessment triangle” that starts with research-based models of cognition and learning [NRC (2001 argue that the educator’s professional development in assessment should focus on understanding assessment principles, designing effective assessments, data analysis, differentiation, feedback, and grading, using formative assessment techniques, integrating technology for assessment purposes, and considering ethical and legal considerations. These components help educators to design assessments that align with learning objectives, interpret data, differentiate between students, provide constructive feedback, use formative assessment techniques, integrate technology for data management, and ensure ethical and legal considerations. By addressing these areas, professional educator development can improve assessment practices and enhance student learning outcomes.

Over all, academic literature highlights the need for new assessment models, focusing on a broader range of skills and competencies, while considering psychological constructs and digital technologies. The call for competency-based assessment addresses flaws in current models, such as standardised tests and bias. The professional development of educators is crucial for aligning assessments with learning objectives and leveraging technology for improved outcomes. Collective efforts to reform assessment practices are vital for a more comprehensive and effective educational system.

## **New Forms of Assessment**

During the last few years, we have observed that both lifelong and informal learning are becoming important themes due to the ubiquitous delivery of information and knowledge. Much of the academic learning happens beyond the formal institutional education systems. It comes from different informal channels on the web. It is also crucial to address what today’s students need. As stressed in the Leuven/Louvain-la-Neuve Communiqué of

Bergan and Matei (2020), '[s]tudent-centred learning requires empowering individual learners, new approaches to teaching and learning, effective support and guidance structures and a curriculum focused more clearly on the learner.' This implies a need for new learning and assessment models that

- foster lifelong and informal learning perspectives;
- support a wide variety of learning experiences within and beyond the institutional boundaries;
- put the student at the centre and give them control over the learning experience;
- recognise the social and network aspect of learning, and put a strong emphasis on knowledge creation and sharing within a social context; and
- operate in decentralised and open environments.

Student-centred and networked learning models are best represented by PBL (project-based learning) approaches. In PBL, students can generate new knowledge and acquire new skills based on their previous knowledge and experiences when they carry out a project. PBL is also a good way for students to solve practical problems in an open environment using an interdisciplinary approach. The shift to new learning models raises challenges in the assessment of learning. Student-centred and networked learning require new assessment models that address recognising and evaluating self-directed, informal, and networked learning achievements. We need to think about new criteria for assessment that bring together educator assessment, peer-assessment, self-assessment, intelligent feedback, and group assessment.

Assessment constitutes an important part of the learning process. Assessment methods are shaped by mainly two factors: The type of assessor and the type of assesses. The assessor is the actor who performs the correction, i.e., evaluates the student's contribution to generate feedback. Four main types of assessors can be distinguished: Educator (educator assessment), peers/network (peer/network-assessment), self (self-assessment), and computer (automatic assessment). The students who are assessed and evaluated by the assessor are known as assesses. There are two main types: Individuals (individual assessment) and groups

(group assessment). Assessment is considered to be an important aspect of both distance and face-to-face education. We can distinguish three main categories of assessment that can be used in any education programme:

- *Diagnostic assessment* provides an indicator of a student's aptitudes and preparedness for a course.
- *Formative assessment* provides feedback to students on their progress but does not contribute to the overall assessment.
- *Summative assessment* provides a measure of achievement or failure in a student's performance concerning the programme of study.

At the beginning of a learning process, it would be good to use diagnostic assessment to find out which prerequisite competence and knowledge students have, to be able to organise student groups and provide appropriate resources and activities to each student according to their profile. At the end of the learning process, a summative assessment would be fitting to provide information to the students about progress and achievement. This form of assessment can be qualified as an 'assessment of learning,' and would enable one to check whether the learning objectives have been achieved. The last type of assessment is formative assessment, which is used to identify the development of students' skills and knowledge. On the one hand, it is considered an 'assessment for learning,' since the assessment activity can be considered a learning activity and an integral part of the inquiry process. On the other hand, formative assessment can be characterised as 'assessment as learning,' in order to give students information on their own learning and assessment and to develop and support meta-cognition for students. All of these forms of assessment are essential to an understanding of what students learn during a learning activity. Researchers have also identified another category of assessment that can be considered transversal to the three categories presented: Authentic assessment. Authentic assessment is related to the assessment of students' skills and competencies in real-world contexts.

The challenge is to provide a thorough assessment of the learning experience, which combines different assessment forms. These include the following:

- *Educator assessment*: Formal learning scenarios are often characterised by a specific separation of students and educators. These roles are often adapted directly, meaning that both educators and students are assessors. The advantages of this method are that the educators' professional expertise as well as their routine practice with assessment, facilitate high-quality feedback with ensured reliability.
- *Peer/Network assessment* involves students making judgements about other students' work. Using peer assessment with essays is useful and highly informative for the student and the tutor and it can be used at various points in the learning and assessment process to give feedback before completing the final piece of work for submission. Peer assessment can be divided into peer-review and peer grading (Gušić, Cardeña, Bengtsson, & Søndergaard 2016). The process of providing elaborated formative feedback to review the performance of other students is called peer review. Peer grading emphasises the process of providing summative feedback or rather grades for peers' work.
- *Self-assessment* involves students judging prerequisites to their work. Reflecting and assessing their performance support self-critical thinking.
- *Automatic assessment/Intelligent feedback* aims to provide students with individualised, dedicated feedback based partly upon an analysis of the procedures followed by the user, which may provide some assistance on how the user should progress.
- *Group assessment*: An approach to reduce the workload for correction is the arrangement of groups to cooperatively work on activities. A more important objective of group assessment is to improve learning success for all group members. Additionally, group assessment provides opportunities to strengthen soft skills like communication skills or conflict management.

- *Mobile assessment* can be defined as an assessment that is facilitated and enhanced by the use of digital mobile devices such as smartphones and tablets and that can be characterised by a rapid and continuous change of context. In particular, mobile and personalised assessment provide efficient and personalised routes for establishing the proficiencies of students. This type of assessment offers students the possibility to maintain and expose their competency profile to multiple learning and assessment environments throughout their lives.
- *Assessments based on OSRQs* (open short response questions) are issues for which the student must provide a short answer, which can be composed of a few words or sentences, not exceeding five lines. The fact that it only requires a single piece of information as a response sets it apart from short development questions in particular. This type of question is easy to produce, provided that it is well constructed and allows for the evaluation of the ability of problem analysis. Intelligent feedback provides interesting information that is generated based on data about the user's interests and the learning context.

Technologies used to facilitate assessment can be split into three categories:

- *Technologies for aligned assessment*: These technologies allow the alignment of assessment with the intended learning outcomes by making possible scenarios in which students can demonstrate the competencies they have developed in authentic contexts (Aguirre, Grau, Eckert, Euzenat, Ferrara, Van Hague, Hollink, Jiménez-Ruiz, Meilicke, & Nikolov 2012). This is facilitated by advanced learning technologies including digital games, mobile technologies, and pervasive learning scenarios.
- *Technologies for embedded assessment*: These technologies enable the integration of assessment activities into learning flows, where the result of the assessment may condition the following learning activity to be presented to the students (Villasclaras-Fernández, Hernández-Leo, Asensio-Pérez, &

Dimitriadis 2013). Technologies supporting personalisation or adaptive learning, the use of interoperability specifications, and standards can offer relevant approaches for embedded assessment.

- *Technologies for scalable assessment:* These technologies are especially critical in courses with no constraints on class size (e.g., MOOCs). Assessment technologies supporting feasible assessment in massive online environments include quizzes embedded in videos, as well as self-assessment and peer assessment systems (Kay, Reimann, Diebold, & Kummerfeld 2013).

### **Self-Assessment and Peer Assessment**

Self-assessment and peer assessment are increasingly recognised as essential tools for nurturing responsible, critical, and reflective professionals within HE (higher education). Recent research underscores the efficacy of these methods when conducted anonymously *via* online platforms, surpassing the effectiveness of traditional lecturer assessments. For instance, a study conducted at the Universidad de Vigo in Spain (Iglesias Pérez, Vidal-Puga, & Pino Juste 2022) found a robust agreement between peer and lecturer assessment, indicating that students possess the capability to evaluate their peers effectively with both validity and reliability.

Topping (1998) and the theoretical underpinnings of the method are discussed. A review of the developing literature follows, including both process and outcome studies. This indicates that peer assessment is of adequate reliability and validity in a wide variety of applications. Peer assessment of writing and peer assessment using marks, grades, and tests have shown positive formative effects on student achievement and attitudes. These effects are as good as or better than the effects of teacher assessment. Evidence for such effects from other types of peer assessment (of presentation skills, group work or projects, and professional skills offers a comprehensive typology of peer assessment methods, laying the theoretical groundwork for their implementation. Stelmakh, Shah, and Singh (2021) address the

detection of strategic behaviour in peer assessments, developing a statistical framework to counter manipulation. Double, McGrane, & Hopfenbeck (2020) and Li, Xiong, Hunter, Guo, and Tywoniw (2020) demonstrate that peer assessment significantly improves student performance, a benefit further enhanced by rater training. The role of peer assessment in fostering self-assessment is underscored by To and Panadero (2019) who have found that peer interactions enhance self-assessment capabilities. Exploring another facet of peer assessment, Zhou, Lin, and Zhao (2022) highlight the importance of respect and constructive feedback in peer assessment, linking them to students' emotional responses and satisfaction. Zheng, Zhang, and Cui (2020) have established that technology-facilitated peer assessment markedly improves learning outcomes, especially when combined with additional support strategies. In this context, Chien, Hwang, and Jong (2020) explore the impact of SVVR-based (scientific visualisation and virtual reality) peer assessment for EFL (English as a foreign language) students, noting improvements in language skills, motivation, and critical thinking while reducing learning anxiety.

Turning to the realm of self-assessment, recent studies have shed light on its dynamics and implications. Yang, Chen, Flanagan, and Ogata (2022) found a positive correlation between frequent self-assessment engagement, and HE scores. However, they also noted that not all active engagement in self-assessment leads to improved learning outcomes, highlighting the complexity of student engagement and behaviour in the self-assessment process.

Further expanding the scope, Surahman and Wang (2022) have conducted a comprehensive literature review focusing on AD (academic dishonesty) and TA (trustworthy assessment) in online education. Findings underscore the necessity for educators to adapt their teaching and assessment methods in the digital age, suggesting the potential of AI, ML, and LA (learning analytics) as pivotal tools in mitigating academic dishonesty and enhancing the trustworthiness of assessments. In a related vein, Darvishi, Khosravi, Sadiq, and Gašević (2022) some common concerns and criticisms are associated with the use of peer assessments (eg, scarcity of high-quality feedback from peer

student-assessors and lack of accuracy in assigning a grade to the assessee underscore the potential of AI and analytical methods in augmenting the reliability and efficiency of peer assessment procedures. This perspective is corroborated by the research of Swiecki, Khosravi, Chen, Martinez-Maldonado, Lodge, Milligan, Selwyn, and Gašević (2022) as well as Hooda, Rana, Dahiya, Shet, and Singh (2022), who simultaneously acknowledge the intricate challenges introduced by the integration of AI in assessment processes and its capacity to yield innovative and efficacious solutions. Collectively, these scholarly insights accentuate the escalating significance of AI in redefining assessment practices, enhancing their dependability, and ensuring their congruence with the requisites of modern education.

### **Project-Based Learning Assessment**

PBL represents a student-centred teaching approach that empowers students to engage collaboratively in authentic projects rooted in real-world scenarios, to develop knowledge and skills relevant to the practical application of the subject matter (Chen & Yang 2019). These projects should be complex assignments that extend beyond textbook content, requiring students to explore, collaborate, and apply new knowledge (Apeanti & Odei-Addo 2024).

In the realm of PBL, students actively participate in the analysis of a given project and the quest for potential solutions, typically tied to the practical aspects of the course material. Marsiti, Santyasa, Sudatha, and Sudarma (2023) elucidate the advantages of incorporating PBL within blended learning frameworks. Their research highlights the substantial role this approach plays in augmenting academic achievements and nurturing creativity among learners. In a related investigation, Umar and Ko (2022) have conducted an in-depth analysis of the synergistic interplay among PBL strategies, the dynamics of team cohesion, and the principles of flipped learning. Their study focuses on understanding the cumulative effect of these educational components on the efficacy and engagement levels of student learning. Additionally, in an endeavour to expand the application scope of PBL, Susanti, Rachmajanti, Suryati, and

Astuti (2023) undertook a study in the domain of English language instruction. Their research was primarily aimed at enhancing the development of critical thinking abilities within online learning platforms.

The PBL setting offers learners a collaborative and context-driven learning experience (Amamou & Cheniti-Belcadhi 2018). Research conducted by Mhlongo, Oyetade, and Zuva (2020) indicates that PBCL (project-based collaborative learning) has a positive impact on students' overall academic performance and the development of their skills. This approach contributes significantly to boosting students' self-confidence as it allows them to engage in collaborative work, explore new concepts, and apply their knowledge in innovative ways.

Collaborative learning represents a multifaceted educational approach that intricately combines individual and group efforts. As highlighted by Johnson and Johnson (2009), it places significant emphasis on two critical aspects: Individual accountability and positive interdependence. In this approach, students' success is not solely reliant on their personal learning but is also intricately linked to the accomplishments of their peers. It is imperative to stress the necessity of a comprehensive assessment of each facet of collaborative learning to effectively cultivate successful collaboration.

### **Lifelong and Informal Learning Assessment**

Research on lifelong learning and informal learning assessment emphasises the significance of acquiring knowledge beyond formal schooling and day-to-day encounters. Informal learning, especially in situations that are abundant in technology, is associated with the development of problem-solving abilities. The implementation of a lifelong learning explorer framework facilitates the delineation of courses and the assessment of methodologies. Harrison, Villalba-Garcia, Brown, and Richardson (2022) mentions that evaluating and assessing lifelong and informal learning is an essential component of both educational and professional growth as it involves recognising and evaluating the knowledge, skills, and competencies gained through non-

formal and informal experiences. The process entails the identification, documentation, assessment, and certification of certain learning outcomes and competencies. The EU (European Union) advocates for the recognition of non-formal and informal learning, highlighting the importance of offering many learning routes that do not lead to dead ends. Authenticating these experiences can result in complete or partial certifications, which can have a favourable influence on professional opportunities, personal growth, and overall welfare. Research on lifelong learning and informal learning assessment emphasises the significance of acquiring knowledge beyond formal schooling and everyday experiences. Informal learning, especially in situations that are abundant in technology, is associated with the development of problem-solving abilities. The implementation of a lifelong learning explorer framework aids in the establishment of a curriculum and the assessment of methodologies.

The 21<sup>st</sup> century has significantly impacted education, emphasising lifelong learning and self-realisation, and exploring the concept of lifelong learning through various scales and assessments (Eskici & Özkır 2023). These include the contribution of local newspapers to lifelong learning, employee attitudes towards lifelong learning, lifelong learning competency scales, and informal learning scales. These assessments assist in guiding educational policies and practices, ensuring individuals' motivation and self-directedness, while learning outcomes are effectively measured and assessed.

Nguyen and Walker (2016) emphasise the importance of preparing students for future learning without compromising their ability to meet present needs. They mention that sustainable assessment is crucial for lifelong learning, aiming to align assessment practices in universities to support students' development as lifelong learners, and this approach goes beyond improving HE to prepare students for future learning, including informal and lifelong learning. Nguyen and Walker (2016) add that new assessment methods are being used to incorporate lifelong learning into Australian education. These methods, including action research, portfolio assessment, and peer assessment, put the student first, focus on learning development, and try to make

assessment more natural in the learning environment, showing how lifelong learning is being put into practice.

Both lifelong and informal learning assessment are critical for educational progress, as they encourage knowledge acquisition outside of formal education. Sustainable assessment approaches integrate universities with lifelong learners, promoting both professional and personal growth. Australian teacher education uses innovative assessment methods to ensure seamless integration.

### **Challenges in New Assessment Models**

The concepts of lifelong learning and informal learning assessment are closely connected, requiring the development of creative methods for assessment. Considering the increasing complexities of the 21<sup>st</sup> century, it is essential to modify assessment model frameworks to maintain education as a catalyst for personal development and societal adaptability. If we would like to modify the new assessment model frameworks, we need to identify the challenges that face them.

Toomey, Chapman, Gaff, McGilp, Walsh, Warren, and Williams (2004) explain the challenges facing the assessment, especially for the Australian Faculty of Education, which faces several challenges, including resistance, marginalisation, student attitudes, time constraints, a lack of communication, regulatory constraints, and philosophical differences. These factors prevent the adoption of novel assessment methods because colleagues frequently find them impractical. Additionally, both time and structural constraints make it difficult to reform assessment systems. Furthermore, philosophical differences within faculties and across campuses further complicate the process.

Guangul, Suhail, Khalit, and Khidhir (2020) explain that the shifting to remote assessment during the COVID-19 epidemic posed difficulties such as infrastructure issues, breaches of academic integrity, student dedication to submitting assessments, and guaranteeing accurate assessment of module learning results. According to them, sufficient infrastructure, encompassing internet connectivity and suitable gadgets, is considered vital for

students and faculty. They mention the imperative to prioritise academic integrity in remote assessments due to the potential of cheating and fraud in the absence of physical supervision. Furthermore, it is essential to address the level of dedication that students have towards participating in online lectures and completing assessments to successfully achieve the desired learning outcomes of the module in a remote learning setting.

Serutla, Mwanza, and Celik (2024) mention that the primary obstacle associated with online assessments pertains to their reliability and authenticity, which is a major challenge because of the prevalence of cheating and impersonation. The issue of technological proficiency poses a significant challenge and a substantial obstacle, impacting the capacity of both students and educators to actively participate. Also, the proctoring tools and monitoring technology give rise to concerns over privacy. Resource limitations, educational adaptation, and interoperability therefore all present difficulties. Personalised feedback and policy frameworks are crucial for the efficacy of online examinations. After all these challenges, the scholars point out that providing personalised feedback and establishing policy frameworks are essential for the success of online assessments.

The interrelated notions of both lifelong learning and informal learning assessment require the use of new assessment methods. To effectively navigate the challenges of the modern day, it is essential to make a significant change in the frameworks used for assessing educational models. This change is necessary to ensure that education continues to promote personal development and the ability of society to adjust to new circumstances.

## **Semantic Web for Intelligent Assessment**

The semantic web is a framework designed to enable data to be shared, to be interconnected and reused across diverse applications. It provides structured data formats and ontologies that facilitate interoperability between systems, especially useful in educational settings where adaptive, personalised learning experiences are key. In an AI-driven educational environment, the semantic web supports advanced content recommendation,

learning analytics, and adaptive assessments by establishing a shared data language and linking data to create meaningful connections. The semantic web offers tools and infrastructure for semantic representation employing ontologies. It provides a common framework allowing data to be shared and reused across applications, enterprises, and communities (Berners-Lee, Hendler, & Lassila 2023). In the past few years, the relevance of semantic web technologies for developing e-learning systems has been supported by several research efforts (Bittencourt, Isotani, Costa, & Mizoguchi 2008). Semantic web technologies have been increasingly used as a tool for generating, organising, and personalising e-learning content, including e-assessment (Cubric & Tosic 2011). The use of ontologies for context modelling in many research works explores the relation between semantic web technologies and context modelling. In practical settings, ontologies have become widely used for mobile context modelling since they are reusable and sharable. In Yu, Zhou, and Nakamura (2008), a context-aware ubiquitous learning infrastructure called semantic learning space is proposed. The infrastructure leverages semantic web technologies to support explicit knowledge representation, flexible context reasoning, and adaptive content recommendation. Semantic web technologies, especially ontologies, have also been used as an efficient modelling approach to propose an exhaustive learner model called 'learner context' (Laroussi 2012).

To deal with these challenges, it is necessary to retrieve relevant data for learning and assessment activities from different tools. Unfortunately, social media applications are data silos – only people may have access to data, not computers. The reuse and exchange of data among social tools are only possible using the API (academic performance index). The semantic web provides a common framework that allows data, information, and knowledge to be shared and reused across applications. Linked data describes a method of exposing, sharing, and connecting data, information, and knowledge on the web (Bojārs, Breslin, Finn, & Decker 2008; Gruber 2008). It provides a standardised, uniform, and generic method for data discovery, distributes queries against several

data repositories, integration, or semantic mash-up, and uniform access to metadata, data, information, and knowledge.

### **Ontological Models for Technology-Enhanced Assessment**

To ensure interoperability at the semantic level, it is necessary to use common vocabularies among web tools. These vocabularies can be semantic models necessary to design technology-enhanced learning systems. In previous work, we described the required semantic models for the description of Assessment (Cheniti-Belcadhi, Henze, & Braham 2008).

According to Baker (2000), the models indicate three main roles in educational processes in AIED (artificial intelligence in education) research. These models could be the following components as ontologies:

- Models as scientific tools: A model used as a means for understanding and predicting some aspects of an educational situation.
- A model as a component: A computational model, corresponding to some aspect of the teaching or learning process, used as a component of an educational artifact.
- A model as a basis for design: A model of an educational process, with its attendant theory, forming the basis for the design of a computer tool for education.

In TEA (technology enhanced assessment), we recall the following models that can be components as ontologies: Learner models, tutor models, assessment models, context models, adaptation models, and recommendation models. The semantic web approach enables us to meet the challenge of finding information by avoiding polysemy and reducing the number of results. The semantic web offers tools and infrastructure for semantic representation employing ontologies. The latter fosters interoperability at the semantic level because it provides a unique meaning for a concept and a relation in ontology. In TEA, the objective is to facilitate assessment and additional potential benefits associated with semantic web technologies. Indeed, ontologies can provide a precise semantic for the assessment

domain, the assessment activities, the different categories of stakeholders, the assessment content that is collected and produced, the assessment context, and all peer assessment activities and components (e.g., criteria and grid).

### **Personalisation and Adaptation in AI Assessments**

Within the continuously advancing domain of educational technology, the incorporation of AI into the realm of assessment methodologies is increasingly recognised as a critical factor in enhancing and personalising educational experiences. ML, a fundamental subdivision of AI, endows systems with the capability to autonomously learn from data. This function is essential for tailoring educational content and assessments within adaptive learning frameworks. Personalisation with AI in learning environments is mainly related to the ability of AI systems to personalise learning processes and provide recommendations to individual students based on their preferences, behaviour, and context. The goal is to improve the learner experience, engagement, and effectiveness by delivering relevant and targeted learning content or services.

Adaptive assessments have emerged as a valuable tool in educational research, offering several advantages. These assessments dynamically adjust their difficulty levels based on students' responses, resulting in more precise knowledge measurements. Consequently, students benefit from tailored feedback, which in turn leads to enhanced performances. Furthermore, adaptive assessment, which is intricately designed by AI, proficiently modulates assessment content, pacing, and complexity in response to the unique performance metrics of each student, thereby ensuring a deeply individualised assessment trajectory. Additionally, ITSs (intelligent tutoring systems), utilising AI, are adept at providing personalised instruction and feedback, effectively mirroring human tutoring approaches.

In the sphere of data analysis, the utilisation of AI in assessment analytics is instrumental in deriving significant insights from assessment data, consequently enhancing the precision and effectiveness of assessment procedures.

The principle of personalisation, lying at the heart of these technological advancements, guarantees that the assessment journey is meticulously aligned with the distinct needs and capabilities of each student.

## **Frameworks for AI-Driven Assessment**

The educational landscape has witnessed a significant transformation, predominantly propelled by the integration of technology into pedagogical settings. This integration has led to remarkable enhancements in the delivery and assessment modes of education, challenging and reshaping traditional educational frameworks. A significant innovation in this domain is the advent of the intelligent assessment framework or framework for AI-driven assessment. It represents the forefront of innovation by integrating educational technology with advanced AI, signifying a departure from conventional assessment approaches.

### **Developing and Implementing AI Assessment Frameworks**

The intelligent assessment frameworks are uniquely dynamic and conceptualised to cater to the individualised learning requisites of each student (Rivera Muñoz, Ojeda, Jurado, Peña, Carranza, Berríos, Molina, Farfan, Arias-González, & Vasquez Pauca 2022). These frameworks are proficient in the real-time processing of performance data, enabling modifications in aspects such as question difficulty, content type, and overall assessment strategies. Such adaptability ensures that each assessment is not only rigorous but also aligns with the individual needs and capabilities of each student (Hill, Overton, Kitson, Thompson, Brookes, Coppo, & Bayley 2020). These frameworks can instantly process and adapt to performance data, which change different aspects of assessment. This ensures that each assessment is not only difficult but also directly related to each student's specific needs and skills (Conati & Merten 2007).

The impact of these intelligent assessment frameworks in the modern educational paradigm is noteworthy, marking a substantial progression in the approach toward learning and assessment. They tackle some of the major hurdles in e-learning,

including the need for personalised learning, engagement, and effective assessment of learning outcomes (Zhang, Zhang, Fang, Wan, Tao, & Sun 2020). As educational landscapes continue to change and diversify, particularly with the growth of online and remote learning formats, the importance of such intelligent systems in delivering high-quality, individualised education on a large scale becomes even more crucial.

### **Case Studies of Framework Implementation**

This section presents two case studies, each exemplifying the integration of AI in distinct educational assessment frameworks. These studies highlight how AI technologies are being leveraged to transform and enhance assessment methodologies in various learning environments.

## **Case Study: Application of AI in the Collaborative Assessment Analytical Framework in Project-Based Collaborative Learning**

### **Framework Overview**

This case study by Hadyaoui and Cheniti-Belcadhi (2022) examines CAAF (the collaborative assessment analytical framework), highlighting its integration of AI in the realm of PBCL. This framework represents a sophisticated approach to assessing student collaboration and interaction in real-world project scenarios, particularly in the context of computer science education.

CAAF is an innovative framework that incorporates AI to enhance the assessment of group dynamics and performance in PBCL. It focuses on real-world problems in programming courses, leveraging AI to analyse and predict student engagement and performance.

### **Framework Implementation**

- *Framework design:* CAAF is designed to assess skill mastery through collaborative projects. AI is utilised to analyse a series of sub-objectives and corresponding assessment activities, addressing the complexities of group work assessment.
- *AI in formative assessment:*
  - *Self-group assessment:* AI algorithms analyse feedback and interactions within discussion forums, providing insights into individual contributions and the effectiveness of internal group feedback.
  - *Peer-group assessment:* AI is used to evaluate interactions in peer-group assessment sessions held in chatrooms. It assesses the quality of peer feedback and its impact on the group's project, influencing the final grading.

- *Data analytics and predictive modelling:* The framework of CAAF employs AI-driven data analytics to organise and interpret assessment data. This includes:
  - *Predicting group disengagement:* AI models predict potential disengagement within groups, allowing timely interventions by educators.
  - *Performance analytics:* The framework uses supervised learning methods to analyse forum contributions and chatroom interactions, generating predictive models of group performance.
- *AI's role in enhancing learning outcomes:*
  - *Educator feedback and decision making:* AI analytics provide educators with comprehensive data, aiding in informed decision-making and targeted feedback.
  - *Student engagement and skill development:* The AI-driven insights assist in enhancing student engagement and developing critical collaboration skills.

The integration of AI into the framework of CAAF marks a significant advancement in educational technology, particularly in PBCL environments. By harnessing the power of AI for data analysis and predictive modelling, CAAF provides a robust, efficient tool for educators to assess and improve group dynamics and individual performance in collaborative projects. This case study showcases the potential of AI to transform educational assessment methodologies, making them more adaptive, insightful, and effective in addressing the challenges of modern collaborative learning settings.

## Case Study: AI-Driven Intelligent Collaborative Assessment Framework in e-Learning Environments

### Framework Overview

In this case study by Hadyaoui and Cheniti-Belcadhi (2023), we examine ICAF (the intelligent collaborative assessment framework), a cutting-edge construct developed to redefine assessment practices and collaborative learning within e-learning platforms. This framework is distinguished by its integration of AI technologies, aimed at refining online learning assessments with a nuanced approach.

### Structure and Functionality of ICAF

- *Framework composition:* Central to ICAF's efficacy is the integration of AI and ML algorithms. These advanced technologies are pivotal in providing personalised feedback and supporting interactive learning activities among students.
- *Modules of assessment and collaboration:* ICAF encompasses two principal modules: The first is an assessment module utilising AI algorithms to deliver tailored feedback to students; the second is a collaborative module designed to facilitate group activities and peer-to-peer learning, thereby augmenting the interactive dimensions of e-learning.

### Target Audience and Operational Environment

- *Intended user demographics:* ICAF is primarily designed for use by educators, instructional designers, and professionals in the field of e-learning. It additionally offers advanced collaborative assessment tools and personalised feedback options for students.
- *Application context:* Tailored for digital e-learning environments, ICAF is adept at navigating the unique challenges and leveraging the opportunities inherent in these settings.

## **Implementation and Application of the Intelligent Collaborative Assessment Framework**

- *Role in assessment process:* ICAF operates across various stages of the assessment cycle. It transcends traditional roles of administering and scoring assessments by also contributing to the formulation of assessment tasks, delivering nuanced feedback, and monitoring student progression.
- *Ongoing assessment and feedback:* The framework is designed for continuous assessment, providing perpetual feedback to students. This aligns with the iterative nature of the learning process, ensuring consistent engagement and development.

## **Purpose and Advantages of the Intelligent Collaborative Assessment Framework**

- *Objective:* ICAF's primary objective is to address the limitations found in conventional e-learning assessment methods. It aims to streamline and elevate the assessment process, integrating AI to foster both collaborative and personalised learning experiences.
- *Benefits:* Employing an AI-driven methodology, ICAF enhances the efficiency and student-centricity of assessments. It stimulates active participation and tailors educational experiences to individual student needs.

## **Impact of AI on the Intelligent Collaborative Assessment Framework**

- *Personalised feedback:* AI's application within ICAF allows for the provision of customised feedback, adapting to the unique learning styles and requirements of each student.
- *Supporting collaborative learning:* AI algorithms are utilised within the framework to analyse group dynamics, significantly contributing to effective peer learning and collaborative engagement.

This case study elucidates the transformative capability of AI integration in modernising traditional assessment methods,

rendering them more adaptive, engaging, and suitable for current e-learning scenarios. With its emphasis on personalisation and collaboration, ICAF establishes a new standard in the application of AI in educational technologies.

## **Generative AI and its Impact on Assessment**

In the dynamically advancing domain of e-learning, the advent of Gen-AI (generative AI) has been recognised as a pivotal development. Scholarly research, like that of Liao, Lu, Fei, Gu, and Huang (2024) including inefficient design processes, limited data reuse, and the underutilization of previous design experience. Generative artificial intelligence (AI) has been instrumental in delineating the capabilities of Gen-AI in the sphere of structural design, especially in its application to generating innovative concepts by analysing complex structural drawings and amalgamating various knowledge sources. Concurrently, Chiu (2023) has undertaken an in-depth analysis of the ramifications of Gen-AI tools like ChatGPT (Chat Generative Pre-Trained Transformer) on conventional educational paradigms, elucidating both the potentialities and challenges inherent in their deployment.

In the current academic conversation, which is mostly about making policies and finding good ways to grade students, there is a big gap in research about how HE will change in the future when AI is involved. To bridge this gap, a qualitative investigation has been conducted, focusing on student perceptions regarding the influence of Gen-AI within the HE sector. This study, predicated on a systematic literature review for the development of a conceptual framework, engages in a thematic analysis of inputs by 51 students. This analysis has unearthed three principal themes alongside 10 subthemes that comprehensively encapsulate the dualistic nature of opportunities and challenges presented by AI in the educational sphere. The findings of this study advocate for a transformative shift in HE, gearing it towards equipping students for a workforce increasingly reliant on Gen-AI.

In a related vein, the research conducted by Miyazaki, Murayama, Uchiba, An, and Kwak (2024) focuses on ChatGPT,

a renowned component of the GPT (generative pre-trained transformer) series, acclaimed for its sophisticated intelligence and conversational proficiency. Their study, which encompasses an analysis of three million Twitter posts from January 2019 to March 2023, underscores a burgeoning interest in Gen-AI across a diverse array of professional fields, extending beyond the confines of information technology. Notably, the general sentiment towards AI has been observed to be positively inclined, correlating directly with the degree of AI exposure, although concerns have been raised by illustrators regarding the unethical application of AI in creative domains.

Furthering this discourse, Baidoo-Anu and Owusu Ansah (2023) have identified ChatGPT as a prominent Gen-AI instrument within the educational arena, acclaimed for facilitating personalised learning experiences, generating stimuli for formative assessments, and providing continuous pedagogical feedback. However, they also delineate certain limitations of ChatGPT, including the potential for disseminating erroneous information, inherent biases in data training, and privacy issues. They posit that a concerted effort involving policymakers, researchers, educators, and technology specialists is imperative to navigate the safe and constructive utilisation of Gen-AI instruments like ChatGPT in educational contexts. Additionally, their reference to a survey on unsupervised generative models for data analysis and representation learning further enriches the discourse on this emergent technology.

Expanding upon the established corpus of research that delineates both the possibilities and limitations inherent in the application of Gen-AI within educational and evaluative frameworks, our study endeavours to deepen this comprehension through empirical investigation. To achieve this objective, a thorough survey has been executed, purposed to collate a wide array of viewpoints regarding the influence of Gen-AI on assessment methodologies. This survey extensively explores the varied applications, advantages, and potential pitfalls associated with the use of Gen-AI across different domains.

## **Analysis of ‘Generative AI in Assessment’ Survey**

Within the sphere of educational technology research, the ‘Gen-AI in assessment’ inquiry was rigorously structured to capture a broad spectrum of viewpoints on the influence of Gen-AI on modern assessment techniques. This extensive study traversed various professional sectors, thoroughly examining aspects such as demographic profiles, the degree of awareness and understanding of Gen-AI, its practical applications in assessment processes, and the perceived advantages and challenges linked to its deployment.

### **Demographic Analysis**

The demographic composition of the study’s participants was notably varied, covering a wide range of ages, gender identities, and professional fields, including education, technology, business, and healthcare. This heterogeneous mix provided a solid analytical base, with diverse experiences in AI technology adding depth to the research findings.

### **Awareness and Interpretation**

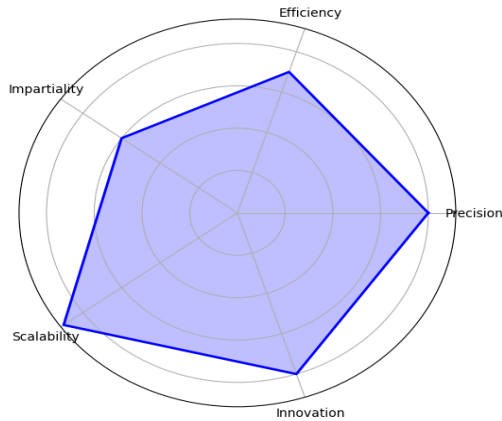
The research revealed a range of levels in terms of awareness and comprehension of Gen-AI among the study’s participants. Varied sources, including academic publications, digital courses, and diverse media platforms, contributed to shaping the participants’ perceptions and attitudes regarding the integration of AI in assessment contexts.

### **Implementation in Current Assessments**

The gathered data pointed to an emerging yet non-uniform incorporation of Gen-AI within current assessment methodologies, with its usage visible in forms like multiple-choice examinations, essay compositions, performance-related tasks, and peer assessments. This trend suggests a progressive, intermittent assimilation of AI technologies into assessment protocols.

### Perceived Advantages

There was a consensus among participants on the potential of Gen-AI to significantly augment the precision, efficiency, and impartiality of assessment procedures.



**Figure 6.1:** Perceived advantages of generative AI in assessments (Personal archive)

The chart, as depicted in Figure 6.1, includes five key aspects: Precision, efficiency, impartiality, scalability, and innovation. Each aspect is rated on a scale of one to 10. These characteristics underscore AI’s transformative capacity to transition towards more dependable and equitable assessment methodologies.

### Ethical and Operational Challenges

The study underscored significant ethical dilemmas, alongside concerns about the accuracy and dependability of AI and the possible hazards of its misuse or excessive dependence. These findings highlight the critical need for ethical foresight and operational prudence in AI’s application within educational frameworks.

### **Future Orientation and Attitudinal Trends**

Participant responses regarding future applications and the assimilation of AI in assessment practices were largely positive, reflecting a general optimism about the progressive role of AI in reshaping assessment techniques. Nevertheless, apprehensions about its impact on established assessment methods were observed, indicating the necessity for a judicious and balanced approach to AI adoption.

### **Additional Insights and Future Research Directions**

The participants offered significant additional insights and put forward suggestions for future research and practical implementation. These inputs are crucial in guiding forthcoming policy development and in fostering the creation of more efficient and innovative assessment methodologies in the context of Gen-AI.

## **Challenges and Ethical Considerations in AI Assessments**

Investigations into Gen-AI within the field of educational assessments shed light on a scenario characterised by both promising innovations and the need for meticulous deliberation. The blend of affirmative attitudes toward future AI integration, coupled with a recognition of the challenges, suggests that while the potential of Gen-AI is recognised, its application in education warrants a careful, ethically grounded approach. This study plays a pivotal role in informing subsequent research directions and policymaking in the rapidly evolving domain of AI-enhanced educational assessments.

### **Challenges in AI Assessments**

The integration of AI into the assessment process represents a noteworthy departure from traditional methodologies, ushering in a more efficient, objective, and personalised approach to measuring students' knowledge and skills.

AI has firmly established itself as a central element within educational environments, ushering in a transformation in the dynamics of teaching and learning. This section delivers an extensive overview of AI's deployment in educational contexts, unveiling specific instances that illustrate its potential for a profound change in the assessment process. Table 6.1 serves as a succinct guide to the myriad applications of AI in education, delineating the purpose of each application alongside its corresponding use case, thereby spotlighting AI's capacity to revolutionise teaching and learning across a spectrum of scenarios.

**Table 6.1:** AI applications in assessment

<b>Application of AI in Education</b>	<b>Description</b>	<b>Use Case</b>
<b>Personalised Assessment</b>	AI-driven platforms adapt content, pace, and difficulty based on individual student needs and preferences.	Students receive customised assessment experiences, enhancing engagement and knowledge retention.
<b>Automated Grading</b>	AI-powered systems automatically assess and grade assignments, quizzes, and exams using ML.	Educators save time on manual grading, and students benefit from quicker feedback, promoting timely improvements in their work.
<b>Intelligent Assessment Systems</b>	AI algorithms create and administer assessments that adapt to each student's proficiency level.	Assessments become more precise and fair, providing tailored challenges to each student, and promoting deeper learning.
<b>Language Learning Support</b>	AI applications assist language students with pronunciation, grammar, and vocabulary through interactive exercises.	Language students receive immediate feedback and targeted practice, accelerating their language acquisition.

<b>Application of AI in Education</b>	<b>Description</b>	<b>Use Case</b>
<b>Predictive Analytics for Student Success</b>	AI-driven predictive analytics analyse student data to identify those at risk of falling behind and suggest interventions.	Educational institutions can proactively support struggling students, increasing overall student success rates.
<b>Educational Chatbots</b>	Chatbots with AI and natural language processing capabilities provide students with instant answers to queries and guidance on academic matters.	Students receive immediate support outside regular office hours, fostering a responsive and supportive learning environment.
<b>Virtual Labs and Simulations</b>	AI-driven virtual labs and simulations create interactive, hands-on learning experiences for science and engineering subjects.	Students gain practical experience in a safe virtual environment, enhancing their understanding of complex concepts.
<b>Assessment Content Recommendation</b>	AI algorithms recommend additional assessment resources based on a student's current assessment progress and interests.	Students discover supplementary materials that check their understanding and cater to their evolving interests.
<b>Adaptive Textbooks</b>	AI-powered adaptive textbooks provide tailored content and practice exercises based on individual learning patterns.	Students receive targeted support and practice materials that align with their strengths and weaknesses.
<b>Proctoring and Anti-Plagiarism Tools</b>	AI tools monitor online exams, ensuring academic integrity by detecting plagiarism and unauthorised assistance.	Educators can conduct secure online assessments, maintaining the credibility of the assessment process.

As e-learning environments continue to transform, the role of AI in assessment is poised for increased prominence, contributing significantly to the development of intelligent and adaptable learning experiences. Table 6.2 serves as an illuminating resource, shedding light on AI's transformative potential in the assessment landscape. It succinctly outlines the critical facets of AI in

assessment and assessment within e-learning environments, emphasising the advantages and benefits inherent in AI-driven assessment tools and personalised assessment methodologies.

**Table 6.2:** Transforming assessment and feedback with AI advancements

Aspect	AI in Assessment and Assessment
Automated Grading and Feedback Generation	Efficiency and timeliness in grading and feedback provision. Consistency and objectivity in assessment outcomes. Scalability for handling large volumes of assessments. Generation of specific feedback and improvement recommendations.
Personalised Assessment	Adaptive assessments tailored to individual proficiency levels. Individualised assessment pathways based on strengths and weaknesses. Support for both formative and summative assessment approaches. Continuous assessment for ongoing feedback and growth opportunities.

### Ethical Implications

There are specific ethical issues with the use of AI tools in student assessments. The two most important ones are justice and bias. Biases in training data may be reflected in students' assessments. Ongoing efforts should be made to detect and lessen these prejudices in order to guarantee justice. Understanding the foundation for assessment depends on the AI's decision-making mechanisms being transparent. As assessment personalisation relies mainly on student data, ethical considerations related to privacy and security become important and crucial. Indeed, we need to ensure and guarantee that the personalised assessment process is conducted in a responsible and transparent way.

### **Ethical Issues in the Use of Student Data**

The utilisation of student data in personalised assessment necessitates a careful balance between enhancing educational processes and protecting privacy. The ethical dimension of this balance demands rigorous attention. To this end, this discourse advocates for the strict enforcement of data protection measures, emphasising the critical importance of maintaining student confidentiality and building trust within educational paradigms. The safeguarding of sensitive student data is not merely a regulatory requirement but a fundamental aspect of ethical educational practice.

### **Ensuring Responsibility and Transparency**

The ethical integrity of personalised assessment processes hinges on their accountability and transparency. This chapter underscores the need for establishing clear, robust norms and standards to govern the use of AI and data analytics in educational contexts. These standards are designed to ensure that the personalisation of learning and assessment adheres to ethical principles, encompassing fairness and impartiality. The goal is to create a framework where personalised assessments are not only effective but also ethically sound and respectful of student privacy and rights.

### **Frameworks for Ethical Data Governance**

Addressing these ethical concerns requires more than *ad hoc* measures; it calls for the development of well-structured data governance frameworks. Such frameworks should encompass recommendations for regular audits, ensuring transparency in algorithmic decision-making, and facilitating the involvement of a broad range of stakeholders in oversight roles. The objective of these frameworks is to establish a system where ethical considerations are ingrained in every aspect of personalised assessment, from data collection to the application of AI-driven insights.

In addition, Remian (2019) offers a thorough examination of the ethical factors associated with the integration of AI

in education and explores a range of obstacles and moral considerations, such as privacy, security, prejudice, impartiality and equality, verification of knowledge, openness, manipulation of people, preservation of cultural values, human control, ownership of ideas, and reliance on technology. These factors are of utmost importance when integrating AI into educational environments to guarantee ethical and efficient support for both students and educators.

### **Future of AI in Educational Assessment**

The educational landscape is currently undergoing a significant transformation, driven by the integration of AI. This shift heralds the transition towards educational experiences that are increasingly personalised, ethically grounded, immersive, and collaborative. In these realms, AI is fundamentally reconfiguring the way in which education is perceived, delivered, and experienced. Furthermore, the emphasis on lifelong learning accentuates AI's pivotal role in fostering environments conducive to sustained education and skill development, a critical aspect in the context of a rapidly evolving global milieu.

Considering assessment can automate the assessment data collection and analysis process, giving educators more time to concentrate on instruction and intervention. AI is also capable of personalising diagnostic and formative assessment by offering personalised, real-time feedback tailored to each student's particular learning requirements. Concerning summative assessment, with AI this type of assessment becomes more reliable. AI can be used, for example, to mark essays, eliminating the subjectivity and inconsistent nature of human grading.

Within this transformative landscape, Gen-AI emerges as a key agent of change, redefining educational experiences to meet the demands of a digitally focused society. This development surpasses mere technological progression, indicating a profound shift in educational philosophies and methodologies. Consequently, the future of education is contingent upon the integration of Gen-AI's technological prowess with the core pedagogical objectives of the educational sector. This integration

ensures that these advanced systems are ethically robust, universally accessible, and in alignment with the requisites of a digital era.

As Gen-AI continues to advance and become more ingrained in educational infrastructures, it is imperative for stakeholders to critically engage with these technologies. This engagement involves not only comprehending the capabilities and prospects of Gen-AI but also addressing the ethical nuances and ensuring equitable access across the board. Such engagement is fundamental in the development of educational practices and assessment methods that are not only effective and inclusive but also adaptable and forward-thinking. These practices and methods are designed to cater for the dynamic requirements of students in a global landscape characterised by rapid change and technological evolution.

## **Conclusion**

After analysing the role of AI in assessments within AI-enhanced learning environments, it is clear that integrating AI into educational assessment mechanisms brings about a major shift in the educational framework. AI has the potential to greatly improve the accuracy, customisation, and efficiency of assessments, leading to a more adaptable, inclusive, and effective era in education.

The shift towards learner-centred educational models, highlighted by the growing prevalence of open and collaborative learning platforms, has necessitated a thorough reassessment of conventional assessment methods. Utilising AI tools, the incorporation of student self-assessment, peer-assessment, project-oriented learning assessments, and assessments of informal learning experiences serve to address the diverse skill sets needed in the modern era. Additionally, this approach fosters a more comprehensive and continuous learning process.

It is anticipated that the utilisation of AI in the realm of educational assessment will experience substantial growth in the coming years. However, AI assimilation and processing of educational data pose major dangers to the privacy and integrity

of such sensitive information, making student data privacy a critical problem. An effective resolution of ethical concerns requires collaboration among professionals from diverse fields such as technology, education, ethics, and policymaking. Our objective is to develop and apply ethical norms and standards for instructional AI. This collaborative and multifaceted strategy ensures that AI technologies are used responsibly and effectively to improve educational outcomes while keeping to the highest ethical standards.

The integration of AI into educational assessment is currently in its early stages. As advancements in these technologies continue, we are at the forefront of an educational revolution that promises to provide tailored, captivating, and effective learning experiences for a wide range of students.

## References

- Aguirre, J.L., Grau, B.C., Eckert, K., Euzenat, J., Ferrara, A., Van Hague, R.W., Hollink, L., Jiménez-Ruiz, E., Meilicke, C., & Nikolov, A. 2012. Results of the ontology alignment evaluation initiative 2012. *Proceedings of the 7<sup>th</sup> ISWC Workshop on Ontology Matching*, 73-115.
- Amamou, S. & Cheniti-Belcadhi, L. 2018. Tutoring in project-based learning. *Procedia Computer Science* 126:176-185. <https://doi.org/10.1016/j.procs.2018.07.221>
- Apeanti, W.O. & Odei-Addo, M. 2024. Technology adaptation in distance teacher training: The impact of demographic factors on learners' technology adaptation. *International Journal of Research* 10(4):776-798. <https://doi.org/10.46328/ijres.3501>
- Baidoo-Anu, D. & Owusu Ansah, L. 2023. Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI* 7(1):52-62. <https://doi.org/10.2139/ssrn.4337484>
- Baker, M.J. 2000. The roles of models in artificial intelligence and education research: A prospective view. *International Journal of Artificial Intelligence and Education Research* 11:122-143.

- Bergan, S. & Matei, L. 2020. The future of the Bologna process and the European higher education area: New perspectives on a recurring topic. In Curaj, A., Deca, L., & Pricopie, R. (Eds): *European higher education area: Challenges for a new decade*, 361-373. Cham: Springer. [https://doi.org/10.1007/978-3-030-56316-5\\_23](https://doi.org/10.1007/978-3-030-56316-5_23)
- Berners-Lee, T., Hendler, J., & Lassila, O. 2023. The semantic web: A new form of web content that is meaningful to computers will unleash a revolution of new possibilities. In Seneviratne, O. & Hendler, J. (Eds.): *Linking the world's information: Essays on Tim Berners-Lee's invention of the world wide web*, 91-103. 1<sup>st</sup> ed. New York: Association for Computing Machinery. <https://doi.org/10.1145/3591366.3591376>
- Bittencourt, II., Isotani, S., Costa, EdeB., & Mizoguchi, R. 2008. Research directions on semantic web and education. *Interdisciplinary Studies in Computer Science* 19(1):60-67.
- Bojars, U., Breslin, JG., Finn, A., & Decker, S. 2008. Using the semantic web for linking and reusing data across Web 2.0 communities. *Journal of Web Semantics* 6(1):21-28. <https://doi.org/10.1016/j.websem.2007.11.010>
- Bonfield, CA., Salter, M., Longmuir, A., Benson, M., & Adachi, C. 2020. Transformation or evolution?: Education 4.0, teaching and learning in the digital age. *Higher Education Pedagogies* 5(1):223-246. <https://doi.org/10.1080/23752696.2020.1816847>
- Chen, C-H. & Yang, Y-C. 2019. Revisiting the effects of project-based learning on students' academic achievement: A meta-analysis investigating moderators. *Educational Research Review* 26:71-81. <https://doi.org/10.1016/j.edurev.2018.11.001>
- Cheniti-Belcadhi, L., Henze, N., & Braham, R. 2008. Assessment personalization in the semantic web. *Journal of Computational Methods in Sciences and Engineering* 8(3):163-182. <https://doi.org/10.3233/JCM-2008-8302>
- Chien, S-Y., Hwang, G-J., & Jong, MS-Y. 2020. Effects of peer assessment within the context of spherical video-based virtual reality on EFL students' English-speaking performance and learning perceptions. *Computers & Education* 146(3). 103751. <https://doi.org/10.1016/j.compedu.2019.103751>

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- Chiu, TKF. 2023. Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence* 6:1–9. <https://doi.org/10.1016/j.caeai.2023.100197>
- Coiro, J. 2021. Toward a multifaceted heuristic of digital reading to inform assessment, research, practice, and policy. *Reading Research Quarterly* 56(1):9–31. <https://doi.org/10.1002/rrq.302>
- Conati, C. & Merten, C. 2007. Eye-tracking for user modeling in exploratory learning environments: An empirical evaluation. *Knowledge-Based Systems* 20:557–574. <https://doi.org/10.1016/j.knosys.2007.04.010>
- Cubric, M. & Tomic, M. 2011. Towards automatic generation of e-assessment using semantic web technologies. *International Journal of E-Assessment* 1(1). 9 pages.
- Darvishi, A., Khosravi, H., Sadiq, S., & Gašević, D. 2022. Incorporating AI and learning analytics to build trustworthy peer assessment systems. *British Journal of Educational Technology* 53(4):844–875. <https://doi.org/10.1111/bjet.13233>
- Double, KS., McGrane, JA., & Hopfenbeck, TN. 2020. The impact of peer assessment on academic performance: A meta-analysis of control group studies. *Educational Psychology Review* 32(2):481–509. <https://doi.org/10.1007/s10648-019-09510-3>
- Eskici, M. & Özkır, B. 2023. Lifelong learning as a measurement tool. *The Journal of Limitless Education and Research* 8(2):253–296. <https://doi.org/10.29250/sead.1272284>
- Gruber, T. 2008. Collective knowledge systems: Where the social web meets the semantic web. *Journal of Web Semantics* 6(1):4–13. <https://doi.org/10.1016/j.websem.2007.11.011>
- Guangul, FM., Suhail, AH., Khalit, MI., & Khidhir, BA. 2020. Challenges of remote assessment in higher education in the context of COVID-19: A case study of Middle East College. *Educational Assessment, Evaluation and Accountability* 32(4):519–535. <https://doi.org/10.1007/s11092-020-09340-w>

- Gušić, S., Cardeña, E., Bengtsson, H., & Søndergaard, HP. 2016. Adolescents' dissociative experiences: The moderating role of type of trauma and attachment style. *Journal of Child & Adolescent Trauma* 9(4):341-351. <https://doi.org/10.1007/s40653-016-0107-y>
- Hadyaoui, A. & Cheniti-Belcadhi, L. 2022. Towards an adaptive intelligent assessment framework for collaborative learning. *Proceedings of the 14<sup>th</sup> International Conference on Computer Supported Education (CSEDU 2022)*, Vol. 1, 601-608. <https://doi.org/10.5220/0011124400003182>
- Hadyaoui, A. & Cheniti-Belcadhi, L. 2023. Intelligent collaborative assessment for cyberspace eLearning environments. *Proceedings of the 2023 International Conference on Cyberworlds (CW)*, 306-313. <https://doi.org/10.1109/CW58918.2023.00054>
- Harrison, C., Villalba-Garcia, E., Brown, A., & Richardson, M. 2022. Conclusion: A way forward on monitoring and evaluation. In Cedefop (Ed.): *Towards European standards for monitoring and evaluation of lifelong guidance systems and services*, Vol. 1, 1-138. Luxembourg: Publications Office of the European Union.
- Hew, KF. & Cheung, WS. 2014. Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational Research Review* 12:45-58. <https://doi.org/10.1016/j.edurev.2014.05.001>
- Hill, M., Overton, T., Kitson, R., Thompson, C., Brookes, R., Coppo, P., & Bayley, L. 2020. 'They help us realise what we're actually gaining:' The impact on undergraduates and teaching staff of displaying transferable skills badges. *Active Learning in Higher Education* 23(1):17-34. <https://doi.org/10.1177/1469787419898023>
- Hooda, M., Rana, C., Dahiya, O., Shet, JP., & Singh, BK. 2022. Integrating LA and EDM for improving students' success in higher education using FCN algorithm. *Mathematical Problems in Engineering* 2022. 12 pages. <https://doi.org/10.1155/2022/7690103>

- Iglesias Pérez, MC., Vidal-Puga, J., & Pino Juste, MR. 2022. The role of self and peer assessment in higher education. *Studies in Higher Education* 47(3):683–692. <https://doi.org/10.1080/03075079.2020.1783526>
- Johnson, DW. & Johnson, RT. 2009. An educational psychology success story: Social interdependence theory and cooperative learning. *Educational Researcher* 38(5):365–379. <https://doi.org/10.3102/0013189X09339057>
- Kay, J., Reimann, P., Diebold, E., & Kummerfeld, B. 2013. MOOCs: So many learners, so much potential.... *IEEE Intelligent Systems* 28(3):70–77. <https://doi.org/10.1109/MIS.2013.66>
- Kayembe, C. & Nel, D. 2019. Challenges and opportunities for education in the fourth industrial revolution. *African Journal of Public Affairs* 11(3):79–94.
- Laroussi, M. 2012. Ontology in adaptive learning environment. In Uden, L., Corchado Rodríguez, ES., De Paz Santana, JF., & De La Prieta, F. (Eds.): *Workshop on learning technology for education in cloud (LTEC'12)*, Vol. 173, 167–177. Heidelberg: Springer. [https://doi.org/10.1007/978-3-642-30859-8\\_16](https://doi.org/10.1007/978-3-642-30859-8_16)
- Li, H., Xiong, Y., Hunter, CV., Guo, X., & Tywoniw, R. 2020. Does peer assessment promote student learning? A meta-analysis. *Assessment & Evaluation in Higher Education* 45(2):193–211. <https://doi.org/10.1080/02602938.2019.1620679>
- Liao, W., Lu, X., Fei, Y., Gu, Y., & Huang, Y. 2024. Generative AI design for building structures. *Automation in Construction* 157:105–187. <https://doi.org/10.1016/j.autcon.2023.105187>
- Marshall, B., Zhang, Y., Chen, H., Lally, A., Shen, R., Fox, E., & Cassel, LN. 2003. Convergence of knowledge management and e-learning: The GetSmart experience. *Proceedings of the 2003 Joint Conference on Digital Libraries*, 135–146. <https://doi.org/10.1109/JCDL.2003.1204854>
- Marsiti, CIR., Santyasa, IW., Sudatha, IGW., & Sudarma, IK. 2023. The effect of project-based blended learning and students' creativity on eleventh-grade students' learning achievement. *International Journal of Instruction* 16(4):805–826. <https://doi.org/10.29333/iji.2023.16445a>

- Mhlongo, S., Oyetade, KE., & Zuva, T. 2020. The effectiveness of collaboration using the hackathon to promote computer programming skills. *Proceedings of the 2020 2<sup>nd</sup> International Multidisciplinary Information Technology and Engineering Conference (IMITEC)*, 1–6. <https://doi.org/10.1109/IMITEC50163.2020.9334089>
- Miyazaki, K., Murayama, T., Uchiba, T., An, J., & Kwak, H. 2024. Public perception of generative AI on Twitter: An empirical study based on occupation and usage. *EPJ Data Science* 13:1–20. <https://doi.org/10.1140/epjds/s13688-023-00445-y>
- Nadelson, LS., Heddy, BC., Jones, S., Taasoobshirazi, G., & Johnson, M. 2018. Conceptual change in science teaching and learning: Introducing the dynamic model of conceptual change. *International Journal of Educational Psychology* 7(2):151–195. <https://doi.org/10.17583/ijep.2018.3349>
- Neuwirth, LS., Jović, S., & Mukherji, BR. 2021. Reimagining higher education during and post-COVID-19: Challenges and opportunities. *Journal of Adult and Continuing Education* 27(2):141–156. <https://doi.org/10.1177/1477971420947738>
- Nguyen, TTH. & Walker, M. 2016. Sustainable assessment for lifelong learning. *Assessment & Evaluation in Higher Education* 41(1):97–111. <https://doi.org/10.1080/02602938.2014.985632>
- Opfer, JE., Nehm, RH., & Ha, M. 2012. Cognitive foundations for science assessment design: Knowing what students know about evolution. *Journal of Research in Science Teaching* 49(6):744–777. <https://doi.org/10.1002/tea.21028>
- Remian, D. 2019. Augmenting education: Ethical considerations for incorporating artificial intelligence in education. *Instructional Design Capstones Collection*. 52. 56 pages. URL: <https://www.semanticscholar.org/paper/Augmenting-Education%3A-Ethical-Considerations-for-in-Remian/10813e9ee301foe3cb6de0404955345bb60dda87>.

## Chapter 6

- Rivera Muñoz, J., Ojeda, F., Jurado, D., Peña, P., Carranza, C., Berríos, H., Molina, S., Farfan, A., Arias-González, J., & Vasquez Pauca, M. 2022. Systematic review of adaptive learning technology for learning in higher education. *Eurasian Journal of Educational Research (EJER)* 98:221-233. <https://doi.org/10.14689/ejer.2022.98.014>
- Sadjadi, EN. 2023. Challenges and opportunities for education systems with the current movement toward digitalization at the time of COVID-19. *Mathematics* 11(2):1-14. <https://doi.org/10.3390/math11020259>
- Secolsky, C. & Denison, DB. (Eds.). 2017. *Handbook on measurement, assessment, and evaluation in higher education*. 2<sup>nd</sup> ed. New York: Routledge. <https://doi.org/10.4324/9781315709307>
- Serutla, L., Mwanza, A., & Celik, T. 2024. Online assessments in a changing education landscape. In Mistretta, S (Ed.): *Reimagining education – the role of e-learning, creativity, and technology in the post-pandemic era*, 1-148. IntechOpen. <https://doi.org/10.5772/intechopen.1002176>
- Stelmakh, I., Shah, NB., & Singh, A. 2021. Catch me if I can: Detecting strategic behaviour in peer assessment. *Proceedings of the AAAI Conference on Artificial Intelligence* 35(6), 4794-4802. <https://doi.org/10.1609/aaai.v35i6.16611>
- Surahman, E. & Wang, T. 2022. Academic dishonesty and trustworthy assessment in online learning: A systematic literature review. *Journal of Computer Assisted Learning* 38(6):1535-1553. <https://doi.org/10.1111/jcal.12708>
- Susanti, A., Rachmajanti, S., Suryati, N., & Astuti, UP. 2023. Online project-based learning and critical thinking skills: A case study in tertiary education. *Proceedings of the International Joint Conference on Arts and Humanities 2022 (IJCAH 2022)*, 992-1002. [https://doi.org/10.2991/978-2-38476-008-4\\_105](https://doi.org/10.2991/978-2-38476-008-4_105)
- Swiecki, Z., Khosravi, H., Chen, G., Martinez-Maldonado, R., Lodge, JM., Milligan, S., Selwyn, N., & Gašević, D. 2022. Assessment in the age of artificial intelligence. *Computers and Education: Artificial Intelligence* 3. 100075. 10 pages. <https://doi.org/10.1016/j.caeai.2022.100075>

- To, J. & Panadero, E. 2019. Peer assessment effects on the self-assessment process of first-year undergraduates. *Assessment & Evaluation in Higher Education* 44(6):920-932. <https://doi.org/10.1080/02602938.2018.1548559>
- Toomey, R., Chapman, J., Gaff, J., McGilp, J., Walsh, M., Warren, E., & Williams, I. 2004. Lifelong learning and the assessment and evaluation practices in some Australian faculties of education. *Journal of In-Service Education* 30(2):225-244. <https://doi.org/10.1080/13674580100200317>
- Topping, K. 1998. Peer assessment between students in colleges and universities. *Review of Educational Research* 68(3):249-276. <https://doi.org/10.3102/00346543068003249>
- Umar, M. & Ko, I. 2022. E-learning: Direct effect of student learning effectiveness and engagement through project-based learning, team cohesion, and flipped learning during the COVID-19 pandemic. *Sustainability* 14(3). 1724. 20 pages. <https://doi.org/10.3390/su14031724>
- Veletsianos, G. & Shepherdson, P. 2016. A systematic analysis and synthesis of the empirical MOOC literature published in 2013-2015. *International Review of Research in Open and Distributed Learning* 17(2):198-221. <https://doi.org/10.19173/irrodl.v17i2.2448>
- Villasclaras-Fernández, E., Hernández-Leo, D., Asensio-Pérez, JI., & Dimitriadis, Y. 2013. Web collage: An implementation of support for assessment design in CSCL macro-scripts. *Computers & Education* 67:79-97. <https://doi.org/10.1016/j.compedu.2013.03.002>
- Wafubwa, R. 2020. Role of formative assessment in improving students' motivation: A systematic review of literature. *The International Journal of Assessment and Evaluation* 28(1):1-17. <https://doi.org/10.18848/2327-7920/CGP/v28i01/17-31>
- William, D. 2011. What is assessment for learning? *Studies in Educational Evaluation* 37(1):3-14. <https://doi.org/10.1016/j.stueduc.2011.03.001>

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- Yang, AC., Chen, IY., Flanagan, B., & Ogata, H. 2022. How students' self-assessment behavior affects their online learning performance. *Computers and Education: Artificial Intelligence* 3. 100058. 8 pages. <https://doi.org/10.1016/j.caeai.2022.100058>
- Yu, Z., Zhou, X., & Nakamura, Y. 2008. Semantic learning space: An infrastructure for context-aware ubiquitous learning. In Sandnes, FE., Zhang, Y., Rong, C., Yang, LT., & Ma, J. (Eds.): *Ubiquitous intelligence and computing*, Vol. 5061, 131-142. Heidelberg: Springer. [https://doi.org/10.1007/978-3-540-69293-5\\_12](https://doi.org/10.1007/978-3-540-69293-5_12)
- Zhang, L., Zhang, D., Fang, J., Wan, Y., Tao, F., & Sun, Y. 2020. Assessment of mental health of Chinese primary school students before and after school closing and opening during the COVID-19 pandemic. *JAMA Network Open* 3:1-4. <https://doi.org/10.1001/jamanetworkopen.2020.21482>
- Zheng, L., Zhang, X., & Cui, P. 2020. The role of technology-facilitated peer assessment and supporting strategies: A meta-analysis. *Assessment & Evaluation in Higher Education* 45(3):372-386. <https://doi.org/10.1080/02602938.2019.1644603>
- Zhou, Y., Lin, S., & Zhao, Q. 2022. Steiner tree-based collaborative learning group formation in trust networks. *Proceedings of the 2022 International Conference on Enterprise Information Systems (ICEIS)*, Vol. 1, 243-250. <https://doi.org/10.5220/0011078800003179>

