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Navigating Artificial Intelligence in Assessment: Academic Professionals' Perceptions of AI Grading in South Africa

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ABSTRACT

This study explores the perceptions of academic professionals in South Africa regarding the use of Artificial Intelligence (AI) in grading within higher education. In the current technological and digital era, the rapid integration of AI tools such as ChatGPT into academic environments points out that there is a growing need to understand how educators engage with these technologies, especially in assessment practices. This study adopted a mixed-methods explanatory design. The study first surveyed 56 academic professionals across diverse disciplines and then conducted semi-structured interviews with five participants to gain deeper qualitative insights. The study findings reveal a generally positive outlook toward AI-assisted grading, with many respondents acknowledging its potential to enhance efficiency, objectivity, and timely feedback. However, significant concerns emerged regarding the loss of qualitative judgment, contextual sensitivity, and the ethical implications of data use. The study highlights a disconnect between institutional support for AI adoption and the lack of structured training for academic staff. Participants expressed a clear preference for a hybrid grading model, combining AI tools with human oversight to preserve pedagogical integrity. Drawing on the Technology Acceptance Model (TAM), the research underscores the importance of perceived usefulness and ease of use in driving AI adoption, while also emphasising the socio-cultural and ethical contexts unique to South African higher education. The study concludes by recommending comprehensive AI training, robust ethical frameworks, and inclusive policy dialogues to ensure responsible, context-aware implementation of AI in assessment. These findings offer critical insights for institutions seeking to balance innovation with educational equity and integrity.

KEYWORDS: Artificial Intelligence, Higher Education, Educational Assessment, Technology Acceptance Model (TAM), South Africa

1. INTRODUCTION

Technology has been an evolving aspect that has changed human life since the advent of the First Industrial Revolution. One important aspect of this technology is artificial intelligence (AI). While AI is appreciated, some segments of society still perceive it as immoral and believe it hinders learner creativity, especially concerning ChatGPT (Dube & Setlalentoa, 2024). One of the major concerns has been primarily about using AI technologies in the education sector, especially by students in their academic assessments (Mulaudzi & Hamilton, 2024). For example, ChatGPT has received a low level of attitude and poor perception among lecturers in developing countries such as Nigeria (Opesemowo, Abanikannda & Iwintolu, 2024). In South Africa, AI technologies are still in early development as students and educators are still trying to fully understand the challenges and opportunities AI brings to the education sector (Patel & Ragolane, 2024). For instance, educators have traditionally assessed student papers to evaluate performance and provide feedback, a process highly valuable for students' academic learning journeys. The introduction of digital technologies in educational assessment has transformed this landscape, offering various interactive methods such as quizzes, online discussions, and multimedia projects (Jonail, 2024). According to Alam and Hasan (2024), AI in education is not merely a technological advancement; it represents a revolutionary approach to teaching and learning, fundamentally redefining the educational landscape. With AI, educators can personalise learning experiences and unlock new possibilities. Furthermore, AI applications enhance the efficiency of learning processes and educational systems, impacting administrative and academic activities such as admissions, counselling, library services, assessment, feedback, and tutoring (Ahmad *et al.,* 2022). Slimi (2023) suggests that AI can assist with grading and assessment, allowing educators to focus on curriculum development and delivering high-quality instruction.

Despite these advantages, significant concerns remain, particularly regarding the use of AI technologies in education in South Africa, where integration challenges persist (Ragolane & Patel, 2024a). For instance, Ragolane and Patel (2024a) found that students hold mixed feelings about AI in education. While AI grading can provide useful feedback for straightforward questions, it struggles with the nuances of more complex assessments (Jonail, 2024). Although AI offers specific, valuable feedback that is appreciated by students, both educators and students express concerns such as educator's worries about losing qualitative insights and maintaining control over the grading process, while students value AI's objectivity but are sceptical about its reliability and the absence of human interaction (Ragolane & Patel, 2024b). Opesemowo, Abanikannda, and Iwintolu (2024) found that while students and staff largely agree on AI's potential to transform higher education, notable disparities exist regarding feedback enhancement, personalisation, critical thinking, and data analysis efficiency in research. Despite this, a 2023 PwC (2023) survey among South African higher education leaders revealed that academic professionals believe AI will play a central role in curriculum design and assessment in the future. The survey indicated that the role of lecturers may evolve into mentoring and supporting learning experiences rather than traditional lecturing.

The ongoing question is the role of lecturers or academic professionals in universities or colleges in the age of AI. The raison d'être of this study is to explore the future of education, particularly in relation to assessment in the era of AI within higher education. A central theme of this study is the exploration of ideals regarding what the future may hold for educational practices. When students are asked about Generative AI, their responses are often tinged with feelings of guilt and shame, a sentiment that extends to lecturers as well. In summary, this study aims to gather the perspectives of academic professionals on AI grading in higher education. It addresses questions such as: (1) Do academic professionals view AI grading as beneficial for education? and (2) Do they believe that assessments should continue to be graded manually? In any case, literature suggests that academic professionals should receive adequate training in AI to equip learners with the necessary skills for future challenges (Slimi, 2023). Although AI can assist with certain grading aspects, there is a broad consensus that it cannot yet replace human judgment, underscoring the need for a hybrid approach that integrates AI and human assessments to improve both efficiency and educational integrity (Jonail, 2024; Ragolane & Patel, 2024b). To this end, considering existing literature and areas for further research, the present study aims to investigate the perceptions of academic professionals regarding the role of AI in grading within South African higher education, highlighting both the potential benefits and the concerns associated with its implementation.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The acceptance of technology, or more broadly, the acceptance of change, presents a significant challenge for individuals and communities alike. Innovations that possess the potential to transform existing practices frequently encounter substantial resistance. This phenomenon can be attributed to various factors, including psychological, social, and economic barriers that individuals and groups face when confronted with alterations to established norms and routines Nicholas-Omoregbe *et al.,* 2018). Understanding the dynamics of this resistance is crucial for effectively facilitating the adoption of new technologies and practices. In 1989, the Technology Acceptance Model (TAM) was introduced as a conceptual framework aimed at elucidating the processes through which users come to accept and utilise new technologies (Davis, 1989). This model has garnered extensive recognition as a foundational tool for understanding the dynamics of user adoption within the realm of technology (Davis, 1989). TAM posits that two principal constructs predominantly influence the acceptance of technology, namely, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). PU refers to the degree to which an individual believes that utilising a specific technology will enhance their job performance or facilitate the execution of tasks more efficiently and effectively (Davis, 1989). PEOU pertains to the extent to which an individual perceives that engaging with the technology will require minimal effort. A technology that is perceived to be user-friendly is more likely to be adopted by users (Davis, 1989). These constructs significantly impact a user's attitude towards the technology, which subsequently affects their behavioural intention to use it. The model further asserts that a favourable attitude, coupled with a strong intention to use, ultimately leads to the actual adoption and utilisation of the technology (Davis, 1989). Through this framework, TAM provides valuable insights into the factors that drive user acceptance and the implications for technology implementation practices. Naarmala (2004) contends that perceived usefulness constitutes a pivotal factor in the adoption of technology within higher education contexts. When users ascertain that a particular technology will enhance their performance or facilitate task execution, their likelihood of adopting that technology increases (Naarmala, 2004). Furthermore, technologies that exhibit benefits in terms of efficiency, effectiveness, and productivity tend to be more readily embraced by users (Naarmala, 2004). The perception of technology use as voluntary rather than obligatory significantly influences user acceptance (Naarmala, 2004). When individuals perceive that they have the autonomy to choose whether to engage with a given technology, they are more inclined to adopt it positively (Naarmala, 2004). Such voluntary use can foster heightened motivation and engagement as users feel a greater sense of control over their learning or work processes. The alignment of the technology with users' specific job functions or academic responsibilities is critical to its acceptance. Technologies that resonate with users' roles are more likely to be seamlessly integrated into their daily routines. Consequently, users are more predisposed to adopt technologies that they perceive as directly relevant to their operational tasks and obligations (Naarmala, 2004). Moreover, observable outcomes stemming from technology usage significantly affect acceptance rates. When users can discern the positive results of their engagement with technology, such as enhanced performance or improved efficiencies, they are more likely to sustain its use. Providing users with constructive feedback and empirical evidence regarding the effectiveness of technology can reinforce its perceived usefulness, thereby facilitating ongoing adoption (Naarmala, 2004). Ragolane and Patel (2024b) emphasise the potential advantages that higher education systems can realise by integrating artificial intelligence. They assert that the adoption of AI can enhance operational efficiency and provide valuable data-driven insights that can significantly improve institutional effectiveness and decision-making processes. To enhance technology adoption in higher education, it is essential to emphasise the demonstration of practical benefits and relevance to users. Presenting explicit evidence of favourable outcomes, alongside ensuring the perception of technology use as voluntary, can markedly improve acceptance rates. Additionally, offering robust training and support systems can aid users in comprehending the advantages and practical applications of new technologies, subsequently increasing their perceived usefulness and relevance. Implementing feedback mechanisms that allow users to track the results of their technology engagement can further reinforce positive perceptions, encouraging sustained interaction with the technology (Naarmala, 2004).

The Technology Acceptance Model (TAM) has evolved to incorporate additional determinants influencing technology adoption, such as social influence and facilitating conditions. These extensions are reflected in the Unified Theory of Acceptance and Use of Technology (UTAUT), which encompasses a broader range of factors affecting user behaviour. In their study, Nicholas-Omoregbe et al. (2018) employed the UTAUT framework to examine technology usage within academic institutions. Their findings underscore the significant role of key variables, including technological acculturation, social influence, and performance expectancy, in shaping user engagement with technology in university settings (Nicholas-Omoregbe et al., 2018). Research on technology acceptance demonstrates that participants generally do not reject technological innovations; however, they express significant concerns regarding various issues, including potential job displacement, fairness, biases, and privacy infringements (Tarisayi, 2024; Ragolane & Patel, 2024a). Furthermore, there are critical legal and ethical implications associated with these concerns, although the issues addressed herein extend beyond the scope of the present study (Ragolane & Patel, 2024a). TAM has faced scrutiny for its inadequacy in forecasting actual technology usage. Empirical evidence suggests that perceived ease of use and perceived usefulness frequently exhibit a lack of correlation with tangible usage behaviours (Ghapanchi & Talaei-Khoei, 2018). Furthermore, existing theoretical frameworks predominantly emphasise the acceptance phase of technology, thereby overlooking the subsequent post-acceptance phase (Ghapanchi & Talaei-Khoei, 2018). This oversight not only limits comprehension of technology utilisation post-adoption but also highlights a critical gap in the literature that warrants further investigation. Ma and Liu (2005), drawing on their examination of the TAM, assert that PU exhibits a consistently strong correlation with technology acceptance. In contrast, PEO shows a comparatively weaker relationship, characterised by less consistency across different contexts. This distinction highlights the critical role of perceived usefulness in influencing individuals' acceptance of technology, while also indicating that the impact of perceived ease of use may vary more significantly depending on the specific circumstances or settings in which technology is implemented. Numerous studies utilising TAM as a foundational framework indicate that individuals generally do not reject technological advancements; rather, they underscore the significance of preserving human oversight and interaction (Pires, Fihlo, & Junior, 2023). In the context of educational assessment, the EU AI Act of 2024 highlights the necessity of human oversight when employing artificial intelligence (AI) to influence the trajectories of students' academic futures. The underlying principle asserts that AI should not serve as the sole arbiter of a student's success or failure. Consequently, AI should not independently determine a student's progression to subsequent levels of their academic career. The EU AI Act categorises AI systems that impact admissions processes, educational level determinations, assessments of suitable educational placements, access, as well as the monitoring and detection of prohibited behaviours during assessments and examinations, as high-risk systems due to their potential to significantly affect students' lives.

3. MATERIALS AND METHODS

The study adopted a mixed-methods methodology, which combines both quantitative and qualitative approaches within a single research effort. Researchers employed mixed-methods research to comprehensively understand a research problem by triangulating data from various sources (Mphahlele, Mbati & Francis, n.d.). In this case, the study adopted a mixed-methods explanatory design. This sequential explanatory design involves first collecting quantitative data and then validating it with qualitative data (QUAN → QUAL). In this process, the researchers first collect and analyse the quantitative data, then use qualitative methods to gain further explanation and interpretation of the quantitative results obtained in the first phase. The analysis of quantitative data would be the primary method of the study. The logic for this approach was that the quantitative data and subsequent statistical analysis provided a general understanding of the issues under investigation. The statistical results were then refined and further explained in the qualitative phase by exploring participants' views in more depth" (Wipulanusat *et al.* 2020).

The study is founded on the premise of two contrasting research paradigms - ontology (how we view reality) and epistemology (how we investigate knowledge), specifically positivism and constructivism/interpretivism. From an epistemological standpoint, positivists assert that the researcher and the world are distinct entities, with the world existing independently of the researcher (Bryman, 2008; Howell, 2013, in Ryan, 2018). Ontologically, they believe in the existence of a single, objective reality that can be discovered through hypothesis formulation and experimental testing based on deductive reasoning, such as observing the occurrence of an event, one can trace back to identify its cause (Ryan, 2018). Positivists argue that knowledge must be developed objectively, without the influences of the researchers' or participants' values (Park et al., 2020). On the other hand, interpretivism provides an entirely different perspective. Interpretivists challenge the positivist assumption that there is a single objective reality, asserting instead that the world is fundamentally social and constructed through social interactions. In this view, reality is shaped by people's perceptions and their interactions with others and the environment. As a result, constructivism and interpretivism are often considered synonymous (Toyon, 2021).

Following the initial quantitative data collection and analysis, the study engaged in a qualitative follow-up phase involving semi-structured interviews with five academic professionals from diverse fields within higher education. These interviews were designed to probe deeper into the trends, uncertainties, and perceptions revealed in the quantitative results. Semi-structured interviews are particularly effective in mixed-methods designs because they allow for focused inquiry while providing flexibility to explore emerging issues (Gill et al., 2008). The selection of participants was based on purposive sampling, aiming to include academic professionals with varying levels of experience in using AI for assessment. This approach is common in qualitative research, where the goal is to gain rich, contextual insights rather than generalisable data (Creswell & Poth, 2018). The interviews were conducted in English, though participants were encouraged to express themselves in their preferred languages, including Sesotho and isiZulu, allowing for culturally grounded responses. Interviews were recorded, transcribed verbatim, and subjected to thematic analysis, a widely used method for identifying, analysing, and reporting patterns within qualitative data (Braun & Clarke, 2006). The analysis followed an inductive approach, allowing themes to emerge naturally from the data, which were then aligned with or contrasted against findings from the quantitative phase.

The qualitative component aligned with a constructivist-interpretivist paradigm, aiming to explore the subjective meanings that academic professionals ascribe to their experiences with AI grading. This paradigm is especially suited to studies seeking to understand attitudes, beliefs, and contextual interpretations within educational settings (Lincoln & Guba, 1985). Ethical approval for the study was obtained from the relevant university ethics committee. Participants in both the quantitative and qualitative phases were informed of the study's purpose, their right to withdraw at any time, and the measures taken to ensure anonymity and confidentiality. Informed consent was obtained electronically for survey respondents and verbally (and recorded) for interview participants. No identifying data were collected, and all responses were anonymised during transcription and analysis. The study adhered to the ethical guidelines for educational research and respected the autonomy, privacy, and dignity of all participants. Particular care was taken when handling interview data, especially where participants chose to express themselves in local dialects or raised sensitive concerns about data privacy and the use of AI technologies.

4. PRESENTATION OF RESULTS

A total of 56 academic professionals participated in the survey. The majority of respondents identified as Lecturers (55.4%), followed by those who chose the general category of Academics (19.6%). Other roles included Professors, Researchers, Administrators, Markers, and a few individuals holding multiple roles such as Adjunct Lecturer, Examiner, and PAC Adviser. This distribution reflects a participant pool primarily involved in teaching and assessment, which aligns closely with the study's focus on perceptions of AI in grading. Respondents represented a wide age range. The largest proportion (42.9%) was aged 40 years and above, followed by 30–40 years (30.4%), 25–30 years (19.6%), and 18–25 years (7.1%). This diverse age distribution reflects a mix of early-career, mid-career, and senior academic professionals, allowing for a nuanced understanding of how perceptions of AI in assessment may vary with professional experience and generational exposure to technology. The gender distribution among participants was relatively balanced, with 53.6% identifying as female and 46.4% as male. No participants selected "Prefer not to say." This near parity provides a solid basis for evaluating whether perceptions of AI in assessment differ across gender lines. Participants came from a wide variety of academic fields, reflecting the interdisciplinary relevance of AI in assessment. The most represented field was Law (12.5%), followed by Economics and Management (5.4%), and other disciplines such as Accounting, Ethical Leadership, Marketing, Social Sciences, HR and IT, each accounting for between 1.8% and 3.6% of the total. This distribution suggests that perceptions of AI grading are being shaped from multiple disciplinary lenses, providing a richer basis for analysis. In terms of academic qualifications, 48.2% of respondents held a master's degree, while 17.9% possessed a Doctorate or PhD, reflecting a highly educated cohort. Additional qualifications included Honours degrees (16.1%), Postgraduate diplomas or certificates (12.5%), and a small number of Chartered Accountants [CA(SA)]. The high level of academic attainment within the sample enhances the credibility of their perspectives on the role of AI in grading and assessment practices. Respondents reported a broad range of teaching experience, from less than one year to over 25 years. The most common response was 3 years (14.3%), followed by 8 years (8.9%). Most respondents clustered within the 3–10-year range, indicating a predominantly early-to-mid-career sample. A small portion of participants reported 25+ years of experience, representing the more seasoned segment of academic professionals. This range of experience provides insights into how familiarity with traditional and digital assessment methods may shape perceptions of AI-assisted grading.

4.1. The Use of AI Tools for Grading

The participants were first asked if they had interacted with or used AI tools for grading assessments for students. From the interview, 50% of participants responded "Yes," indicating a notable level of direct engagement with AI-assisted assessment. Conversely, 42.9% reported "No," while 7.1% were uncertain ("Maybe"), suggesting potential gaps in awareness of what constitutes AI in grading. These findings highlight a transitional moment in higher education, where AI adoption is underway but far from uniform, underscoring the need for increased AI literacy and training.

4.2. Perception Of Academic Professionals on AI Grading

Table 1: Academics' perceptions on AI grading for assessments

Statement	Agree	Disagree	Strongly Disagree	Strongly Agree	Uncertain
I believe AI can enhance the grading process.	22	4	1	20	9
AI provides valuable feedback on student assessments.	23	5	1	13	14
I am comfortable integrating AI tools into my grading practices.	26	4	1	19	6
AI can assess complex assignments as effectively as human evaluators.	15	8	2	8	23
I feel that using AI in grading may lead to a loss of qualitative insights.	21	7	1	13	14
I believe that AI grading can lead to a more objective evaluation of student work.	21	6	2	9	18
I am concerned about the reliability of AI in providing feedback.	22	9	0	11	14
I think AI can help reduce my workload related to grading.	25	4	0	19	8
I would prefer to maintain a hybrid approach, using both AI and human judgment in grading.	15	1	0	36	4

The results of the study reveal a generally positive perception among academic professionals regarding the role of artificial intelligence (AI) in the grading process. A significant majority of respondents (75%) either agreed or strongly agreed that AI has the potential to enhance grading, indicating a widespread belief in its usefulness within higher education assessment. Similarly, around 80% of participants expressed confidence that AI ensures objectivity in grading, highlighting the value placed on fairness and consistency, especially in large or repetitive assessment tasks. These findings align with the core principles of the Technology Acceptance Model (TAM), particularly about perceived usefulness and efficiency. However, attitudes were more divided when it came to AI's capacity to provide valuable feedback. While 64% responded positively, a notable portion (25%) were either uncertain or disagreed. This suggests that while AI is appreciated for standardised tasks, its effectiveness in offering qualitative or formative feedback remains under scrutiny. Furthermore, 41% of respondents agreed that AI cannot consider contextual or subjective elements in student work. A high number of participants (over 40%) were uncertain on this point, indicating a possible lack of exposure to or familiarity with the limitations of current AI tools. This concern speaks to one of the key challenges in automated assessment, its inability to fully grasp nuances such as tone, creativity, or cultural context. Another noteworthy insight is that 61% of participants felt that AI might reduce educators' direct engagement with student work. This reflects an underlying concern that the increased use of AI could diminish meaningful educator-student interaction, a key element in student learning and academic development. The perception that

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AI may interfere with pedagogical relationships and the human aspects of education could act as a barrier to full adoption. Overall, while there is strong support for the integration of AI in grading due to its perceived efficiency and objectivity, the responses also reveal important reservations. These include the need for AI tools to better handle nuanced academic content and the potential risk of disengaging educators from the formative assessment process. The significant number of "uncertain" responses across several items further suggests a need for structured training and institutional support to increase understanding, trust, and effective use of AI in academic assessment.

4.3. AI Grading Integration

Table 2: Academics' perception on AI integration in teaching and learning

Statement	Agree	Disagree	Strongly Disagree	Strongly Agree	Uncertain
I have received adequate training to use AI tools in my grading process.	11	25	4	10	6
AI tools are user-friendly and easy to integrate into my current grading practices.	17	4	1	13	21
I believe that AI can help identify areas where students struggle academically.	25	3	0	13	15
Using AI in grading would encourage me to adopt more innovative teaching methods.	26	3	0	18	9
I feel that AI can facilitate timely feedback to students.	25	1	1	25	4
I believe that AI grading tools can be customised to suit different assessment types.	27	0	0	19	10
I trust AI systems to handle sensitive data related to student performance.	18	5	2	12	19
AI can help in providing personalised learning experiences for students.	28	2	0	15	11
I think that AI grading tools should be subjected to regular reviews and updates to ensure effectiveness.	21	0	0	33	2
I feel that my institution supports the integration of AI in grading adequately.	24	2	0	14	16

The analysis of academic professionals' views on the integration of AI into their grading practices reveals a strong overall optimism, tempered by critical gaps in training and familiarity. Notably, while the majority of respondents believe that AI can play a valuable role in education, more than half (over 50%) indicated that they have not received adequate training to effectively use AI tools in their grading practices. This lack of preparation could hinder meaningful implementation, as familiarity and confidence are essential for adoption. Despite this, many respondents view AI tools as user-friendly and integrative, with 30 individuals agreeing or strongly agreeing with that statement. However, a significant proportion (21 respondents) expressed uncertainty, suggesting that direct experience with AI in grading remains inconsistent across the sample. On a more positive note, 38 respondents agreed or strongly agreed that AI can help identify areas where students struggle academically. This highlights a growing awareness of AI's diagnostic and data-driven capabilities, which can support more targeted intervention and personalised learning. Additionally, there is a strong sentiment that AI can foster pedagogical innovation. 44 participants agreed or strongly agreed that using AI in grading would encourage them to adopt more creative and innovative teaching methods, underscoring the belief that AI is not just a functional tool but also a catalyst for rethinking teaching strategies. Institutional support for AI integration emerged as a major theme, with an overwhelming 89% of respondents (50 out of 56) either agreeing or strongly agreeing that their institutions support AI adoption in grading. This suggests a growing system-level push towards digital transformation in higher education. However, the disparity between institutional support and the lack of personal training highlights a structural disconnect, while policies and systems may endorse AI use, individual readiness is lagging. Overall, the responses in this section indicate a strong professional interest in the educational potential of AI, particularly in enhancing teaching strategies and improving student assessment. However, without adequate training and more widespread exposure, many academic professionals remain cautious or uncertain. This points to a clear need for capacity-building efforts, including workshops, hands-on training, and institutional investment in user education to ensure effective and confident use of AI in academic settings.

To better understand the academic professionals' beliefs on AI grading, the researcher followed up with a qualitative phase of interviews with selected academic professionals in which they were asked about their beliefs on pedagogy through AI, preparedness, institutional support and ethical concerns.

4.4. Lack Of Training and Preparedness

The findings generally revealed that while academic professionals showed a willingness to explore AI in assessment, many felt underprepared due to limited formal training. One academic staff explained,

> *"You know…I have no resistance to using AI in my marking, it is just that I have not received much structured training. I have had to learn through experimentation, which works to a point, but I would prefer a more guided approach. I mean most of the AI technologies really have been a surprise to most academic professionals, of which the majority we hear about them through the media or sometimes from our students"* (Staff 1)

Another reflected,

> *"You see, there is a genuine interest from most of us to incorporate AI tools in meaningful ways, but the support structures need to catch up. Some of us are digital migrants, and onboarding should be more tailored."* (Staff 2)

One participant described their gradual learning journey:

> *"For me, I was hesitant, but I have since found a few tools that help. Still, I believe formal workshops could accelerate adoption and reduce trial-and-error. It's not that we resist AI, we just want to use it responsibly."* (Staff 3)

A lecturer noted,

> *"AI has huge potential, but it's a tool like any other. The more we are trained to understand it, not just use it, the better we'll be able to align it with pedagogical goals."* (Staff 4)

Another added,

> *"With basic orientation, I think many of us would be able to explore AI more confidently. Right now, we're at different stages of familiarity, and that needs to be addressed."* (Staff 5)

4.5. Concerns About Objectivity and Contextual Sensitivity

While AI was commended for its consistency and objectivity, participants expressed thoughtful concern about how it might navigate nuance, especially in more interpretive assignments.

One academic shared,

> *"AI removes bias in some ways, especially when grading large classes. But it also lacks the cultural and contextual understanding that sometimes influences how we interpret a student's work."* (Staff 1)

A lecturer reflected:

> *"I once ran a batch of student essays through an AI tool and saw some real efficiency gains. But I also noticed it didn't quite capture the subtlety in argumentation or expression. It is not that AI gets it wrong, it's that it misses the layers."* (Staff 2)

Another participant observed,

> *"so these things are complicated, but that does not mean we cannot be ahead of the development. For example, for structured responses, AI is fantastic. But in subjects where meaning is inferred or language is nuanced, we still need the human eye. AI can complement us but not replace us. Sometimes AI does not understand where the student is coming from. 'Akukuhle uma umshini engakuqondi ukuthi sifundani ngendlela yethu' [It is not helpful when the machine does not understand how we learn in our way]. That is an important point about cultural learning styles."* (Staff 3)

One academic offered,

> *"I have seen how useful AI can be in streamlining objective grading. But for tasks involving creativity or reflection, I always do a secondary review to ensure fairness."* (Staff 4)

Another staff member summarised it well:

> *"It is not about distrusting AI, it is about recognising that some assessments are layered with context, and that's where the educator still plays a critical role."* (Staff 5)

4.6. Institutional Support Without Capacity Building

Participants acknowledged that their institutions were increasingly supportive of AI adoption but pointed out that this encouragement should be matched with consistent developmental initiatives.

One academic stated,

> *"There is definitely an appetite from leadership to integrate AI into academic processes, and that's encouraging. What we now need is a clear roadmap how to implement it practically in teaching and assessment."* (Staff 1)

A participant explained,

> *"We are moving in the right direction. I have seen AI mentioned in institutional planning documents, and some departments have piloted tools. What would help now is a shared platform or community of practice."* (Staff 2)

Another added,

> *"The infrastructure is slowly coming into place, but for academics to truly engage, we need peer learning and tech champions to lead the way."* (Staff 3)

A lecturer shared,

> *"It is promising to see support from senior management. If we align that with internal training, we will empower staff to experiment responsibly."* (Staff 4)

Another reflected,

> *"I do not think the issue is a lack of support; it is about structured rollout. The interest is there, and with consistent engagement, we will see meaningful adoption."* (Staff 5)

4.7. Reframing Pedagogy Through AI

The participants were also asked has the use of AI had influenced their teaching or assessment methods. Responses reflected that many academics were not only using AI to support grading but were also rethinking pedagogical strategies as a result. One lecturer noted,

> *"Using AI has helped me revisit the purpose of each assessment. It is made me distinguish between tasks that test knowledge and those that develop thinking. That is a powerful shift."* (Staff 1)

Another academic shared,

> *"AI has become a useful pre-marker for me. It does the first pass, especially on objective criteria, and I focus my energy on qualitative feedback. It's like having an assistant, it does not remove me, but it makes me sharper."* (Staff 2)

One participant reflected,

> *"Since using AI tools, I have started introducing more formative assessments. The fast turnaround of feedback allows me to adjust teaching strategies week to week. It is responsive teaching."* (Staff 3)

A lecturer explained,

> *"It allows me to provide earlier feedback, which helps students improve as they go, not just at the end. That improves learning, not just grading."* (Staff 4)

Another added,

> *"AI has not changed what I teach, but it is influencing how I assess. It pushes me to think about what kinds of tasks AI can support, and what still needs the human touch."* (Staff 5)

4.8. Ethical Concerns and Data Sensitivity

The participants were asked about ethical concerns and data sensitivities, particularly around student data, transparency, and AI accountability, which emerged across interviews but were often framed as areas for guidance rather than opposition. One participant noted,

> *"I believe that there is a shared understanding that AI should be handled carefully. I do not oppose its use, but I think we need clearer policies about what happens to the data AI tools collect. 'Kea tshaba hore data ya bana ba rona e ka sebelisoa hampe ke di-machine tsena' [I am afraid that our students' data might be misused by these machines]. The concern reflects a deep mistrust that comes not from resistance to technology, but from a lived awareness of how systems can fail marginalised groups."* (Staff 1)

A staff member elaborated,

> *"I do not believe AI is inherently unethical. But because it deals with student performance data, we need to have clear frameworks on consent, data storage, and accountability. Students should be informed, and academics should be protected too."* (Staff 2)

Another offered a nuanced view:

> *"Ethical concerns do not mean rejection, they mean caution. We are all aware of the potential for bias or error in automated systems. But with checks and transparency, I think these concerns are manageable."* (Staff 3)

One academic commented,

> *"Trust in AI begins with transparency. If we understand how it works and where it concludes from, we can use it more confidently. We just need to be included in that loop."* (Staff 4)

Finally, a participant shared,

> *"Listen, the technology is not the problem, it is how we regulate and communicate its use. With strong policy, training, and feedback loops, AI can be both ethical and effective."* (Staff 5)

5. DISCUSSION OF FINDINGS

The findings of this study reveal a complex and often ambivalent stance among academic professionals regarding the role of AI in grading within South African higher education. While many respondents acknowledged the potential efficiency, consistency, and scalability that AI grading systems offer, concerns persist around the erosion of human judgment, ethical considerations, and the readiness of institutions and educators to adopt such technologies. This mirrors earlier studies such as Ragolane and Patel (2024a), who reported that although students recognised the efficiency and personalisation AI could bring, they also expressed a need for human oversight and consent in the use of AI for assessments. Furthermore, students perceived that full automation in grading might compromise the integrity and depth of educational feedback. These perspectives align with Mulaudzi and Hamilton's (2024) work, which emphasises the importance of balancing AI-enhanced learning with traditional pedagogical methods and the necessity for AI literacy training for both students and staff. Academic professionals echoed similar sentiments. While AI was recognised for reducing administrative burdens and enabling personalised learning, as supported by Ahmad *et al.* (2022), who stated that lecturers remain cautious about the implications for educational quality and their evolving roles in the academic ecosystem. The study's results also resonate with the Technology Acceptance Model (TAM) theoretical lens, highlighting that perceived usefulness (PU) and perceived ease of use (PEOU) significantly influence attitudes toward AI adoption. However, consistent with the critique by Ghapanchi and Talaei-Khoei (2018), actual usage behaviours may not always align with perceived utility, especially when cultural and institutional readiness is lacking. Resistance to AI in education also appears rooted in deeper socio-cultural and infrastructural issues. Dube and Setlalentoa (2024) highlight that, particularly in rural or under-resourced contexts, AI implementation can be viewed with suspicion, perceived as a threat to the humanistic role of educators, or as exacerbating existing educational inequalities.

These concerns are not merely about the technology itself but reflect broader anxieties regarding fairness, bias, and transparency. Additionally, findings from Olawale and Mutongoza (2024) stress the need for ongoing professional development, ethical guidelines, and institutional dialogues to bridge the perception gap between students and staff on AI's role in enhancing learning and research. Their mixed-methods approach confirmed that while consensus exists about AI's transformative potential, differences in expectations and trust levels between students and educators remain a barrier to full acceptance. The findings of this study affirm that artificial intelligence (AI) is fundamentally reshaping educational practices in South African higher education, particularly in assessment and grading systems. Participants in the study generally expressed openness to the integration of AI tools, with a nuanced appreciation for their advantages, chief among them efficiency, feedback consistency, and reduced marking workloads.

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However, these benefits were tempered by a cautious optimism; concerns persisted about fairness, transparency, and the irreplaceable value of human judgment. These mixed sentiments echo the growing body of literature on AI in education. Ragolane and Patel (2025) observed that while students acknowledged AI grading as faster and more consistent than human grading, scepticism lingered due to perceptions of dehumanisation and lack of contextual sensitivity in AI evaluations. This concern aligns with findings from Ragolane, Patel, and Salikram (2024), who discovered that although ChatGPT-4 demonstrated improved accuracy over previous models, it still struggled to replicate the depth and nuance of human markers, especially in evaluating creativity and complex, subjective answers. Furthermore, the socio-technical framework discussed by Ragolane and Patel (2025) underscores that AI implementation is not merely a technical upgrade but a social transformation. This perspective reveals the need to synchronise technological advancement with the human and institutional dynamics of South African higher education.

In this regard, successful adoption hinges not only on software capability but on institutional readiness, staff training, and student empowerment. The current study also reinforces the central claim made by Ragolane and Patel (2024a), which highlights the tension between innovation and ethical considerations in AI deployment. While automation promises scalability and efficiency, stakeholders must navigate critical issues such as data privacy, algorithmic bias, and the psychological impact of AI replacing human roles. Similarly, Ragolane and Patel (2024a,b) called for a hybrid grading model, where AI systems work in tandem with human assessors to preserve the contextual understanding, emotional intelligence, and mentorship inherent in education. Another vital aspect that emerged from both the literature and participant feedback is the role of student agency. Research by Ragolane and Patel (2024b) pointed out that students are more accepting of AI grading when they are involved in decision-making processes and when human oversight is guaranteed. This insight is pivotal in crafting policies that are not only technologically feasible but also democratically grounded.

6. CONCLUSION AND RECOMMENDATIONS

This study set out to explore academic professionals' perceptions of artificial intelligence in grading within South African higher education. The findings confirm a broadly positive outlook towards AI’s potential to improve efficiency, consistency, and feedback mechanisms in assessment. However, this enthusiasm is tempered by persistent concerns over the loss of qualitative judgment, the contextual sensitivity required in grading, and ethical issues surrounding data privacy. These nuanced responses highlight a broader theme within the AI-in-education discourse: while AI may assist in modernising higher education, its adoption cannot come at the expense of pedagogical integrity and human interaction.

The integration of AI into grading has begun to influence pedagogical strategies, prompting educators to rethink assessment design, enhance feedback loops, and adopt more formative learning approaches. Nonetheless, a critical insight from this study is that institutional support for AI integration is not matched by sufficient training or capacity-building efforts. Academic professionals remain unevenly equipped, often resorting to informal or self-directed learning to navigate AI tools. This disjunction between institutional policy and practitioner readiness poses a significant challenge to the responsible and sustainable implementation of AI in academic assessment.

Moreover, this research underscores the need for human-AI collaboration rather than replacement. Educators and students alike are sceptical of full automation, especially in disciplines where subjective interpretation, creativity, and cultural context are vital. A hybrid grading model emerges as a preferred solution, one that leverages AI's efficiency while preserving the educator’s interpretive role. Ethical frameworks and transparency must be embedded in AI policies to ensure accountability and build trust.

In a context such as South Africa's, where historical inequities persist, AI must be deployed with sensitivity to socio-cultural dynamics and institutional disparities.

We can almost (all) agree that AI offers significant potential to transform assessment practices, but its role must be complementary, not substitutionary. Therefore, realising its benefits will require a systemic approach linking institutional vision with educator training, infrastructure development, ethical governance, and student involvement. South African higher education stands at a critical juncture: the opportunity to lead with a pedagogically responsible, culturally grounded, and ethically sound approach to AI adoption is within reach, but only if implementation is deliberate, inclusive, and context aware. Against this backdrop, the study recommends the following:

- **Implement Comprehensive AI Training for Academic Staff**: Institutions should develop structured training programmes tailored to educators' needs and disciplines. Training should not only address how to use AI tools but also focus on ethical implications, data handling, and pedagogical alignment.
- **Adopt a Hybrid Grading Framework**: AI should be used to augment, not replace, human judgment. Institutions should develop policies that require human moderation or review of AI-generated assessments, particularly for assignments involving interpretation, creativity, or critical thinking.
- **Establish Clear Ethical and Regulatory Guidelines**: Universities must create robust data governance policies that address transparency, consent, data storage, and accountability in AI use. These frameworks should reflect global best practices (e.g., the EU AI Act) while being tailored to South African socio-cultural and legal contexts.
- **Promote Inclusive Dialogue and Student Agency**: Students should be engaged in decision-making about AI use in assessments. Regular feedback mechanisms and ethical forums should be institutionalised to ensure that learners understand and trust AI-enhanced processes.

7. DECLARATIONS

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8. REFERENCES

[1] Ahmad, S.F.; Alam, M.M.; Rahmat, M.K.; Mubarik, M.S.; Hyder, S.I. Academic and Administrative Role of Artificial Intelligence in Education. Sustainability 2022, 14, 1101. https://doi.org/10.3390/su14031101

[2] Alam, M. Hasan, M. Applications and Future Prospects of Artificial Intelligence in Education. International Journal of Humanities & Social Science Studies (IJHSSS). 10(10),197-206. DOI: 10.29032/ijhsss.v10.i1.2024.197-206

[3] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

[4]
Creswell, J. W., & Poth, C. N. (2018). *Qualitative Inquiry and Research Design: Choosing Among Five Approaches* (4th ed.). SAGE Publications.
[5] Davis F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, Vol. 13, No. 3, pp. 319-340.
[6] Dube, B., & Setlalentoa, W. (2024). Artificial Intelligence as an opportunity or a curriculum trajectory in the 21st century? Towards embracing unfamiliar discourses. Interdisciplinary Journal of Education Research, 6(s1), 1–09. https://doi.org/10.38140/ijer-2024.vol6.s1.02
[7] European Union. (2024). Artificial Intelligence Act. Official Journal of the European Union, L 1689, 12 July 2024.
[8] Ghapanchi, A. H. & Talaei-Khoei, A. (2018) Rethinking Technology Acceptance: Towards a Theory of Technology Utilization. Towards Technology Utilization Theory. Twenty-fourth Americas Conference on Information Systems, New Orleans, pp 1-9
[9] Gill, P., Stewart, K., Treasure, E., & Chadwick, B. (2008). Methods of data collection in qualitative research: Interviews and focus groups. *British Dental Journal*, 204(6), 291–295. https://doi.org/10.1038/bdj.2008.192
[10] Jonail,K. Artificial Intelligence in Academic Grading: A Mixed-Methods Study. Master's thesis. University of Gothenburg. Available at: https://gupea.ub.gu.se/bitstream/handle/2077/83561/Jona%CC%88ll_HPA202_VT24.pdf?sequence=1&isAllowed=y
[11] Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic Inquiry*. SAGE Publications.
[12] Ma, Q. & Liu, L. (2005) The Technology Acceptance Model. Journal of Organizational and End User Computing, 16(1), 59-72
[13] Mphahlele, R.S., Mbati., L and Semui, F. (n.d). Research Methodology Demystified. Available at: https://uir.unisa.ac.za/bitstream/handle/10500/30527/Research%20Methodology%20Demystified.pdf?sequence=1&isAllowed=y
[14] Mulaudzi, L., & Hamilton, J. (2024). Student perspectives on optimising AI tools to enhance personalised learning in higher education. Interdisciplinary Journal of Education Research, 6(s1), 1–15. https://doi.org/10.38140/ijer-2024.vol6.s1.03
[15] Naarmala, J. (2004). Reflections on Technology Acceptance in Higher Education. ECIS 2004 Proceedings. 136. http://aisel.aisnet.org/ecis2004/136
[16] Nicholas-Omoregbe, O.S., Osabohien, R.A., Ibidapo, D., Omoregbe, N.A., Idemudia, E.C., Mbarika, V.W., & Noguera, J. (2018). A Study of Factors Affecting Technology Usage. Americas Conference on Information Systems.
[17] Opesemowo, O. A. G., Abanikannda, M. O., & Iwintolu, R. O. (2024). Exploring the potentials of ChatGPT for instructional assessment: Lecturers' attitude and perception. Interdisciplinary Journal of Education Research, 6, 1–12. https://doi.org/10.38140/ijer-2024.vol6.21
[18] Park, Y.S., Konge, L., P; Artino, Anthony R. J. (2020). The Positivism Paradigm of Research. Academic Medicine 95(5):p 690-694. DOI: 10.1097/ACM.0000000000003093
[19] Patel, S., & Ragolane, M. (2024). The implementation of artificial intelligence in South African higher education institutions: Opportunities and challenges. Technium Education and Humanities, 9, 51-65.
[20] Pires, P. Fihlo, B. A & Junior, R. C.(2023). Technology Readiness Index: a study applied to students Technology Readiness Index: a study applied to students. AIS Electronic Library, pp1-9
[21] PwC. (2023). Higher Education Leaders Survey Disruption and opportunities in education. https://www.pwc.co.za/en/assets/pdf/high-education-leader-survey-2023-v1.pdf

[22] Ragolane, M., & Patel, S. (2024a). Transforming Educ-AI-tion in South Africa: Can AI-Driven Grading Transform the Future of Higher Education?. Journal of Education and Teaching Methods. Vol.3, Issue 1, pp 26 – 51.

[23] Ragolane, M., & Patel, S. (2024b). Artificial Intelligence, Digital Grades and Human Voices: Students Perceptions on AI Grading in Higher Education. International J. Soc. Sci. & Education. 2024(14), 32-64.

[24] Ragolane, M., & Patel, S. (2025). AI Grading Systems in Education: A Panacea or Drawback for South African Higher Education. *Improving Student Assessment With Emerging AI Tools*, 245-272.

[25] Ryan, G. (2018). Introduction to positivism, interpretivism and critical theory. Nurse Researcher, 25(4) pp. 41–49.

[26] Slimi, Z. (2023). The Impact of Artificial Intelligence on Higher Education: An Empirical Study. European Journal of Educational Sciences, 10(1), 17–33. https://doi.org/10.19044/ejes.v10no1a17

[27] Tarisayi, T.S. (2024) ChatGPT use in universities in South Africa through a socio-technical lens, Cogent Education, 11:1, 2295654, DOI: 10.1080/2331186X.2023.2295654, pp1-10

[28] Toyon, M.A.S. (2021). Explanatory sequential design of mixed methods research: Phases and challenges. International Journal Of Research In Business and Social Science 10(5)(2021) 253-260.

[29] Wipulanusat, W., Panuwatwanich, K., Stewart, R.A., Sunkpho, J. (2020). Applying Mixed Methods Sequential Explanatory Design to Innovation Management. In: Panuwatwanich, K., Ko, CH. (eds) The 10th International Conference on Engineering, Project, and Production Management . Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-15-1910-9_40