WORK-INTEGRATED LEARNING IN THE AGE OF ARTIFICIAL INTELLIGENCE

Equity, Innovation and Partnerships for bridging Theory and Practice

Editor
Cias T Tsotetsi

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EDITORS' PROFILES

Cias T. Tsotetsi
Academic and Research,
University of the Free State, QwaQwa Campus, South Africa
ORCID: https://orcid.org/0000-0003-1035-3339

Prof. Cias Tsotetsi is an Associate Professor and Vice Principal for Academic and Research at the University of the Free State. He has served as the Assistant Dean in the Faculty of Education at the same university until the end of 2024. Cias holds a PhD specialising in Philosophy and Policy Studies in Education. He worked in the schooling environment for approximately 24 years before joining the university in 2010. He has authored and co-authored several research articles and conference papers on community engagement, teacher development, Participatory Action Research methodologies, and Work Integrated Learning, among other topics. He has successfully supervised several postgraduate students to completion. Cias has participated in partnerships and NRF-funded projects with peers from universities such as UKZN, UNIZULU, UNIVEN, DUT, and SPU. In 2025, he successfully completed two projects that were funded by the National Research Foundation (NRF) and the Centre for Teaching and Learning at the University of the Free State.

AUTHORS' PROFILES

Adeniyi Michael Adeduyigbe
Department of Science and Technology Education,
Faculty of Education, University of Ibadan, Ibadan, Nigeria
ORCID: https://orcid.org/0009-0006-4864-2119

Andiswa Ndaliso-Roji
Walter Sisulu University,
Butterworth, South Africa
ORCID: https://orcid.org/0009-0006-3857-2399

Anuoluwapo Elizabeth Adeduyigbe
Department of Special Education, Faculty of Education,
University of Ibadan, Ibadan, Nigeria
ORCID: https://orcid.org/0009-0005-6517-2721

Ayotomiwa Abel Akinde
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
ORCID: https://orcid.org/0009-0008-5295-7441

Bafundi Zealous Mapisa
Continuing Professional Teacher Development,
Faculty of Education, IYunivesithi Walter Sisulu, Mthatha, South Africa
ORCID: https://orcid.org/0000-0002-3194-7921

Bamidele Emmanuel Tijani
Department of Science Education, Faculty of Education,
University of Lagos, Akoka, Yaba, Nigeria
ORCID: https://orcid.org/0009-0009-3466-4140

Brian Shambare
Department of Mathematics, Natural Sciences and Technology Education,
University of the Free State, Qwaqwa, South Africa
ORCID: https://orcid.org/0000-0002-4869-8407

Buhle Stella Nhlumayo
Department of Educational Foundations, College of Education,
University of South Africa, Pretoria, South Africa
ORCID: https://orcid.org/0000-0002-0598-3988

Bunmi Isaiah Omodan
Institute for Open and Distance Learning,
University of South Africa, Pretoria, South Africa
ORCID: https://orcid.org/0000-0002-9093-3108

Cias T. Tsotetsi
Academic and Research,

University of the Free State, QwaQwa Campus, South Africa
ORCID: https://orcid.org/0000-0003-1035-3339

Courage Matobobo
Walter Sisulu University,
East London, South Africa
ORCID: https://orcid.org/0000-0002-7125-5989

Doris Chasokela
Department of Technical and Engineering Education and Training, Faculty of Science and Technology Education,
National University of Science and Technology, Bulawayo, Zimbabwe
ORCID: https://orcid.org/0009-0001-5983-8508

Gardner Mwansa
Walter Sisulu University,
East London, South Africa
ORCID: https://orcid.org/0000-0003-3827-9783

Godswill Ernest Irilochuwe
Department of Science Education, Faculty of Education,
University of Calabar, Cross River State, Nigeria
ORCID: https://orcid.org/0009-0006-7584-5552

Godwin Pedzisai Dzvapatsva
University of Suffolk,
Ipswich, Suffolk, England
ORCID: https://orcid.org/0000-0001-5534-2647

Kudakwashe Manokore
Department of Art Design and Technology,
Faculty of Science and Technology Education,
National University of Science and Technology, Bulawayo, Zimbabwe
ORCID: https://orcid.org/0009-0009-5799-6252

Limkani Sincuba
Continuing Professional Teacher Development,
Faculty of Education, IYunivesithi Walter Sisulu, Mthatha, South Africa
ORCID: https://orcid.org/0000-0002-6033-2029

Matipa Ricky Ngandu
Walter Sisulu University,
East London, South Africa
ORCID: https://orcid.org/0000-0003-4098-5070

Ohunene Florence Omuya
Department of Educational Foundations, Faculty of Education,
Federal University Lokoja, Kogi State, Nigeria
ORCID: https://orcid.org/0000-0002-4288-783X

Oluwatosin Motunrayo Kachi
Department of Arts & Social Sciences Education, Faculty of Education,
Federal University Lokoja, Kogi State, Nigeria
ORCID: https://orcid.org/0009-0000-8949-4913

Omolabake Temilade Ojo
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
ORCID: https://orcid.org/0000-0002-8744-3490

Prince Daughin Ngqabutho Ncube
Walter Sisulu University,
East London, South Africa
ORCID: https://orcid.org/0000-0002-9262-3779

Raymond Nkwenti Fru
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley 8301, Province of the Northern Cape, South Africa
ORCID: https://orcid.org/0000-0002-0507-5269

Refiloe Khitsane
Walter Sisulu University,
East London, South Africa
ORCID: https://orcid.org/0009-0008-4748-9313

Sifiso Everelly Ncube
Department of Childhood Education, Faculty of Education,
University of the Free State, Qwaqwa, South Africa
ORCID: https://orcid.org/0009-0003-5969-6567

Thulasizwe Fredrick Mkhize
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley 8301, Province of the Northern Cape, South Africa
ORCID: https://orcid.org/0000-0002-7910-9724

Tolulope Ayodeji Olatoye
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley 8301, Province of the Northern Cape, South Africa
ORCID: https://orcid.org/0000-0002-2249-9258

RESEARCH JUSTIFICATION

The rapid diffusion of artificial intelligence (AI) into higher education has transformed the conditions under which students are prepared for the world of work; however, scholarly understanding of how these technologies reshape Work-Integrated Learning (WIL) remains fragmented, uneven, and often speculative. This book addresses this gap by assembling a coherent body of original scholarship that examines the intersection of AI and WIL across a range of disciplines, institutions, and national settings. It does not merely survey or summarise existing knowledge; rather, each chapter advances a distinct, evidence-based argument that extends the boundaries of current understanding. Collectively, the contributions constitute the first integrated account of how AI is simultaneously enabling and complicating the pedagogical, ethical, and structural dimensions of WIL, thereby making a genuine and identifiable contribution to an emerging field of inquiry.

The scholarly merit of the collection rests on the originality and methodological rigour of its individual studies. Contributors employ a deliberately diverse set of recognised research approaches, among them bibliometric and systematic literature reviews, qualitative case studies, conceptual and theoretical analyses, and autoethnographic inquiry, each chosen for its capacity to illuminate a specific dimension of AI-mediated WIL. This methodological plurality is not incidental; it mirrors the complexity of the phenomenon and enables the book to generate new empirical findings and fresh theoretical insights rather than restating established positions. Every chapter is grounded in systematic investigation, situates its argument within the relevant literature, and offers conclusions that are defensible, traceable to evidence, and open to scholarly scrutiny.

A distinctive feature of the volume is its sustained and critical engagement with equity, a concern that remains under-theorised in much of the existing literature on WIL and educational technology. Several chapters interrogate the danger that AI-driven innovation, if adopted uncritically, may entrench rather than dissolve existing inequalities, particularly for learners and institutions in rural, under-resourced, and Global South contexts. By foregrounding African and other resource-constrained settings, the book contributes original conceptual and contextual knowledge that is frequently absent from a literature dominated by perspectives from the Global North. This situated analysis represents one of the collection's most significant contributions and responds to a pressing need for research that is both globally relevant and locally grounded.

The book is aimed at a specialist scholarly readership. Its primary audience includes researchers, academics, and postgraduate students engaged in higher education, teacher education, and educational technology, alongside informed practitioners, curriculum designers, and policymakers tasked with shaping WIL in an era characterised by rapid technological change. The depth of engagement with theory, the explicit attention to methodology, and the level of analysis position the work as a resource for advancing scholarly debate, while its practical insights provide evidence-informed guidance for the design, supervision, and governance of AI-enhanced WIL. By deliberately bridging theory and practice, the volume serves both the academic community and the broader objective of strengthening professional preparation.

Furthermore, the scholarly integrity of the collection has been meticulously maintained throughout. Each chapter underwent independent, rigorous peer review and careful editorial curation to ensure adherence to the standards expected of original, peer-reviewed scholarly work. Beyond the quality of its individual components, the book achieves coherence as an intellectual project: its chapters are organised around the interlocking themes of equity, innovation, and partnerships, and they engage with one another in ways that produce a cumulative argument greater than the sum of its parts. Consequently, the volume stands as an original, rigorously reviewed, and demonstrably scholarly work that both consolidates and extends knowledge at the intersection of artificial intelligence and Work-Integrated Learning, and is intended to help shape the research agenda in this field in the years to come.

PREFACE

Artificial intelligence has transitioned, in a remarkably short period, from the periphery of educational discourse to the very centre of our conceptualisation of teaching, learning, and the preparation of students for professional life. Nowhere are the stakes of this shift higher than in Work-Integrated Learning, the domain where the classroom intersects with the workplace and where the promise and perils of new technologies are experienced most acutely. This book was conceived in response to this pivotal moment, stemming from a conviction that the question confronting educators is no longer whether AI will reshape Work-Integrated Learning, but rather how, for whom, and at what cost. It brings together scholars who have chosen to address this question directly, with curiosity, rigour, and a shared commitment to the students and communities their work ultimately serves.

The chapters compiled herein approach the challenge from multiple perspectives. They encompass teacher education, chemistry, information and communications technology, early childhood education, and educational management; they draw on evidence from South Africa, Nigeria, Zimbabwe, and beyond; and they utilise methods as diverse as bibliometric mapping, systematic review, qualitative case study, conceptual analysis, and autoethnography. What unites them is the set of commitments encapsulated in the book's title. The contributors assert that innovation must be pursued thoughtfully rather than embraced uncritically; that equity must remain central, ensuring that AI broadens rather than narrows access to meaningful learning; and that genuine progress relies on partnerships, between institutions and workplaces, between educators and technologies, and across the Global North and the Global South. When considered collectively, the chapters provide both a sober account of the risks and a hopeful, practical vision of what AI-enhanced Work-Integrated Learning could become.

This collection is the result of the generosity, patience, and scholarship of numerous individuals. I am profoundly grateful to the authors, who entrusted their work to this project and responded graciously to the demands of revision; to the reviewers, whose meticulous and constructive engagement strengthened each chapter; and to the ERRCD Forum, whose commitment to open and accessible scholarship has made this book freely available to readers wherever they may be. It is my hope that students, researchers, educators, and policymakers alike will find in these pages both a critical map of our current position and a constructive sense of potential pathways forward. More importantly, I hope the book serves as an invitation, to question, to experiment responsibly, and to continue the dialogue about how artificial intelligence can be harnessed to serve, rather than undermine, the profoundly human endeavour of education.

Cias T. Tsotetsi
Editor

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CHAPTER ONE

Work-Integrated Learning in an AI-Driven Era: A Bibliometric Review of Research Themes and Emerging Trends

Brian Shambare
Department of Mathematics,
Natural Sciences and Technology Education,
University of the Free State, Qwaqwa, South Africa

Corresponding author: ShambareB@ufs.ac.za

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Abstract: As artificial intelligence (AI) transforms the nature of learning and work, higher education faces an urgent challenge. The pertinent question is not whether AI will reshape Work-Integrated Learning (WIL), but rather how institutions can reimagine it for an AI-driven workplace. This reality has incited extensive academic interest, resulting in a global surge of WIL scholarship over the past decade. However, research at the intersection of WIL and AI lacks a coherent synthesis, leaving critical gaps in understanding how intelligent technologies redefine WIL. This chapter addresses this gap by presenting one of the first bibliometric mappings of WIL scholarship in AI-driven contexts. Drawing on 4,975 records from the Web of Science (2015-2025), the chapter examines publication trends, prolific contributors, citation impact, and thematic evolution. The findings reveal an inflection point post-2020, with an increase in publications signalling AI's role as a disruptive catalyst. Thematic analysis indicates a shift from traditional models of WIL practices towards a new paradigm centred on generative AI, virtual internships, and intelligent mentoring. While confirming the continued dominance of traditional WIL research hubs, the analysis highlights the rising influence of East Asian scholarship and a persistent underrepresentation of the Global South. The chapter identifies the convergence of WIL with educational technology research as forming an essential interdisciplinary core. This review underscores the necessity for future research to interrogate AI-integrated WIL models across diverse contexts. From a practical perspective, the findings advocate for the establishment of pedagogical and policy guidelines to support the integration of AI in WIL ecosystems.

Keywords: Work-Integrated learning, artificial intelligence, higher education, bibliometrics, text mining, thematic analysis.

1. Introduction

Work-Integrated Learning (WIL) has long been recognised as a cornerstone of higher education's engagement with the world of work, functioning as a bridge between academic knowledge and professional practice. Commonly operationalised through internships, cooperative education, practicals, and industry placements (Jackson & Cook, 2025; Zegwaard et al., 2023), WIL has played a central role in promoting graduate employability (Ferns et al., 2025), professional identity formation (Hiratsuka, 2026), and work readiness (Wahyuningsih et al., 2025; Pretti et al., 2020). These models have historically relied on relatively stable assumptions regarding workplace roles, supervision, and the nature of professional expertise. While these approaches have been instrumental in aligning higher education with labour market needs, they are now being profoundly unsettled.

The accelerating diffusion of artificial intelligence (AI) across industries is reshaping contemporary work and, by extension, WIL. In this chapter, AI is conceptualised to encompass both the automation of routine and administrative tasks and the utilisation of generative and decision-support tools that mediate knowledge work, supervision, and professional judgement across professional fields such as education, business, engineering, and health. Within WIL, these developments are shifting learning from predominantly place-based, human-mediated models toward digitally enabled, hybrid, and algorithmically augmented forms of engagement (Sellberg & Lindwall, 2026; Wilson et al., 2022). In response, an emerging body of scholarship has begun to interrogate how WIL is being reconfigured in AI-mediated contexts, examining issues such as shifting employability skills (Rowe & Zegwaard, 2017; Safri et al., 2026), virtual internships (Wahyuni et al., 2026), intelligent tutoring systems (Bardach et al., 2025), learning analytics (Wahyuningsih et al., 2025), and simulation-based training environments (Sellberg & Lindwall, 2026; Wood et al., 2020). Collectively, this body of work signals a substantive transformation of WIL from predominantly place-based experiential learning to increasingly digital, hybrid, and algorithmically mediated forms of workplace engagement.

Despite the increasing scholarly interest, research on WIL in the AI era remains highly fragmented. Studies are scattered across various fields, including education (Wahyuningsih et al., 2025; Jackson et al., 2022), workforce development (Dean, 2023), educational technology (Wilson et al., 2022), and computer science (Mousavi et al., 2022). These studies often adopt discipline-specific perspectives and focus on isolated technologies or professional contexts. To date, existing literature reviews on WIL and technology have primarily concentrated on online, remote, or virtual placements in general (e.g., Areskoug Josefsson et al., 2024; Dlamini et al., 2023; Samson et al., 2025), with little attention given to the role of AI in WIL or to mapping the intellectual structure of this emerging field. There are very few, if any, studies that have provided a field-level bibliometric mapping of WIL research specifically addressing AI, including its key themes, knowledge clusters, and emerging fronts across disciplines. This lack of comprehensive synthesis hinders the building of cumulative knowledge and diminishes the ability of institutions and policymakers to respond strategically to AI-induced transformations in WIL.

Simultaneously, the integration of AI into professional environments has broadened WIL beyond traditional physical placements to include AI-mediated mentoring (Sellberg & Lindwall, 2026). For instance, AI-based analytics can monitor student performance in real time, transitioning supervisory practices from solely human mentorship to data-informed or AI-assisted feedback (Bardach et al., 2026). These developments raise critical questions regarding authenticity, supervision, assessment, ethics, and the evolving role of human expertise in WIL—questions that fragmented or discipline-bound analyses alone cannot adequately address. Bibliometric analyses provide a robust means of tackling this challenge. Unlike narrative and systematic reviews, which are limited by their interpretive scope or restrictive inclusion criteria, bibliometric approaches allow for the examination of relational, structural, and evolutionary features of a research domain that remain largely inaccessible through other forms of synthesis (Donthu et al., 2021; Ellegaard & Wallin, 2015; Hood & Wilson, 2001). Such approaches facilitate the identification of influential contributors, dominant knowledge clusters, and emerging research fronts (Börner & Boyack, 2003; Kastrin & Hristovski, 2021), thereby illuminating how a research domain evolves conceptually and methodologically over time. In the context of WIL and AI, a bibliometric lens is particularly valuable given the interdisciplinary nature and rapid expansion of the field.

Against this backdrop, this chapter presents a comprehensive bibliometric mapping of WIL scholarship in AI-driven contexts published between 2015 and 2025. The period from 2015 to 2025 was selected as AI-related applications in education and workplace learning began to scale significantly after 2015, accompanied by a marked expansion in both conceptual and empirical research on AI-mediated WIL. The year 2025 was included as the most recent complete year. As one of the first large-scale, data-driven mappings of this emerging domain, the chapter contributes in three key ways. First, it consolidates a fragmented body of literature into a coherent intellectual framework. Second, it identifies dominant and emergent research themes that illuminate how AI is reshaping the purposes, practices, and assumptions of WIL. Third, it offers evidence-based directions for future research, institutional strategy, and policy development to align WIL with increasingly intelligent workplaces. Importantly, the chapter extends beyond descriptive mapping by interpreting bibliometric patterns as epistemic indicators of how WIL is being re-theorised as a socio-technical learning paradigm in response to AI-driven transformations of work. Accordingly, this chapter is organised around the research questions presented in sub-section 1.2.

1.2 Research questions

To address the study's research questions (RQs), a multi-level bibliometric analysis was conducted, encompassing the temporal, geographic, institutional, authorial, source, and conceptual dimensions of the literature, as outlined in Table 1.

Table 1: *RQs, Units of analysis, and analytical strategies*

RQ	Unit of Analysis	Analytical Strategy
RQ1: How has the volume and scholarly influence of publications evolved?	Temporal trends in field development	Longitudinal descriptive and trend-based analysis
RQ2: Which countries demonstrate the highest research output and citation visibility?	National-level scholarly contributions	Comparative country-level assessment
RQ3: Which institutions are the primary contributors to the field?	Institutional research participation	Institutional productivity influence

RQ4: Which authors exert the greatest scholarly influence within the domain?	Individual researcher productivity and impact	Author-level bibliometrics
RQ5: Which scholarly works have exerted the strongest influence on the field's development?	Highly influential publications	Document-level citation analysis
RQ6: Which journals serve as the most influential publication outlets in terms of citation impact?	Source-level visibility and influence	Journal-level citation performance and impact
RQ7: What dominant themes and keyword structures define the field's intellectual landscape?	Conceptual and thematic organisation of the literature	Co-word analysis and thematic evolution

2. Bibliometric Studies on WIL: A Critical Review

To position the present chapter within existing scholarship, Table 2 synthesises key bibliometric contributions in the field, while also revealing the analytical gaps and limitations that remain unaddressed.

Table 2: *Literature review table*

Study	Data Scope & Period	Analytical Emphasis	Key Insights	Key Limitations
Yoo et al., (2025).	932 articles from Web of Science 1994-2023	Intellectual structure, thematic landscape, and emerging trends.	WIL research shows multidisciplinary growth with emphasis on social/contextual learning dimensions.	Analysis confined to peer-reviewed articles up to 2023.
Areskoug Josefsson et al. (2024)	5323 articles from Scopus; 2000-2023	Bibliographic coupling, co-citation, networks	Steady increase in WIL publications; Australia leads output.	Scopus-only; misses synonyms like work-based learning.
Rafiq et al. (2024)	1392 articles from Scopus; 2002-2023	Comprehensive mapping	Exponential post-2015 growth	Limited to select document types after filtering
Ademuyiwa et al. (2024)	222 articles from IJWIL; 2018-2023	Themes, keywords, citations	Equity (18%), skills (15%); qualitative bias	Single journal scope; low generalisability
Amarathunga (2024)	1295 articles from Scopus 2002-2023	Scientometric trends	Australia, South Africa and Canada emerged as the most productive countries within the field of WIL.	Predictive gaps
Amarathunga et al. (2024	521 articles from Scopus 1975-2023	Mapping trends, productivity, citations, geographic contributions, Bradford's Law, Lotka's Law, and keyword thematic analysis	Shows steady growth; top countries are Australia, the USA, and Canada; future pathways include workplace learning.	Limited to Scopus data and specified software tools.

Gessler et al. (2021	5474 articles from Scopus 2011-2020.	Bibliographic coupling, co-citation analysis and co-occurrence analysis.	Scholars from developing countries and nations are excluded from the international discourse	Limited to Scopus.
Bezerra et al. (2021)	Publications from Web of Science	publication trends over time, research areas, contributing countries, and leading organisations	The UK and Australia lead as the main countries; Monash University and Middlesex University are primary knowledge producers.	Limited to WoS, potentially excluding other databases or non-indexed works.
Moosa & Shareefa (2020	100 most-cited articles from Scopus.	Keyword occurrence, co-authorship networks, and bibliometric coupling networks	Research is rising, with two primary schools: learning communities and communities of practice; top journals link closely to education; calls for more Eastern/Asian contributions.	Relies solely on the Scopus database, potentially missing other sources.
Winchester-Seeto & Rowe (2019)	1,542 articles from Web of Science; 1996-2018	Discipline/journal analysis	Education/business/ health dominance; practice-oriented	Web of Science underrepresents practitioners

2.3 Gaps in the literature and importance of the chapter

Recent bibliometric studies on WIL reveal several persistent limitations. They often cover narrow temporal windows or periods preceding the advent of AI, emphasise descriptive trends over thematic or relational structures, and underrepresent developing and non-Western contexts (Areskoug Josefsson et al., 2024; Yoo et al., 2025; Gessler et al., 2021; Moosa & Shareefa, 2020). While these studies provide useful snapshots of publication patterns, citations, and contributions from various countries or institutions, they remain predominantly descriptive and do not specifically address AI-mediated transformations of WIL. Consequently, they offer limited insight into the underlying intellectual structures, collaboration networks, or emergent research fronts that define the field. This chapter seeks to address these gaps by (a) extending the temporal window to 2025, (b) employing interpretive thematic analysis to transcend mere description, and (c) explicitly analysing the underrepresentation of scholarship from the Global South. Through the interpretation of bibliometric indicators, this chapter not only maps the field but also provides insights into how WIL is evolving in response to AI-driven transformations of work. This endeavour aims to offer a conceptual lens to guide future research, curriculum design, and policy development.

3. Methodology

This chapter adopts a bibliometric research design, integrating bibliometric and text mining techniques to examine the evolution of WIL scholarship in contexts related to AI. In this study, 'AI-related contexts' refer to research that engages with AI technologies, such as machine learning, generative AI, automation, and intelligent decision-support systems, within WIL environments. This definition informed the search strategy discussed in subsection 3.2, where AI-specific keywords were combined with WIL-related terms, and guided the selection of bibliometric indicators (e.g., keyword co-occurrence and thematic evolution). Although bibliometric methods are inherently quantitative and frequency-based (Börner & Boyack, 2003; Donthu et al., 2021; Kastrin & Hristovski, 2021), the study employs an interpretive analytic framework in which indicators function as proxies for intellectual influence, theoretical alignment, and conceptual change. Co-citation networks are interpreted as shared epistemic foundations, keyword co-occurrence as dominant problem framings, and thematic evolution analysis as shifts in the conceptualisation of WIL in relation to AI over time. This design transcends descriptive reporting to generate inferential insights into the field's developmental trajectory. Text mining encompasses a set of computational techniques used to extract meaningful patterns, trends, and insights from extensive collections of textual data (Chen et al., 2023). Text mining was employed to analyse the publications by identifying recurring keywords, thematic patterns, and conceptual trends, thereby complementing bibliometric techniques such as citation and co-authorship analysis.

3.1 Data source and search strategy

Data were retrieved from the Web of Science (WoS) Core Collection, chosen for its stringent journal selection criteria, stable citation indexing, and widespread usage in high-quality bibliometric research (e.g., Zupic & Čater, 2015; Donthu et al., 2021). While relying on a single database may introduce coverage bias, particularly by excluding regional or practice-oriented outlets, we prioritised WoS to ensure analytical consistency and citation reliability. A structured search strategy was employed, combining terms related to WIL, such as work-integrated, experiential, and work-based learning, with keywords associated with AI, including artificial intelligence, machine learning, and automation. The corpus was limited to peer-reviewed, English-language journal articles published between 2015 and 2025, excluding editorials, reviews, and conference papers. Records were screened in two stages. First, titles and abstracts were reviewed to confirm a clear focus on WIL and AI-related tools or contexts. Second, full texts were assessed when relevance was ambiguous. Studies that mentioned AI only tangentially or addressed workplace learning without a WIL or higher education component were excluded. Following this screening process, 4,975 records were retained (Figure 1).

3.2 Bibliometric tools selection

Multiple bibliometric tools were utilised to examine publication trends, intellectual structures, and thematic development within the field, facilitating methodological triangulation across complementary analytical techniques. Descriptive statistics, performance indicators, and analyses of thematic evolution were conducted using the Bibliometrix R package (version R.5.2) and its web interface, Biblioshiny (Aria & Cuccurullo, 2017; Cobo et al., 2011). VOSviewer (version 1.6.20) (van Eck & Waltman, 2010) was employed to visualise co-authorship networks and co-citation structures, thereby enabling robust identification of collaborative patterns and shared intellectual foundations. The network was standardised using the association-strength measure, and clustering was conducted with a resolution parameter of 1.00. Ten random starts and ten iterative refinements were applied to ensure the robustness and stability of the clustering solution. Microsoft Excel facilitated supplementary data management and trend visualisation. The utilisation of multiple tools enhanced analytical robustness by permitting cross-validation of patterns and minimising tool-specific bias.

3.3 Data analysis techniques

Quantitative bibliometric analyses were conducted using science mapping and text mining to capture both performance indicators and structural relationships within the literature (Figure 1). To establish the field's temporal development, we examined publication growth trends and citation trajectories. Citation impact was assessed using total citations, average citations per document, and h-index metrics, providing complementary measures of scholarly influence. To situate this influence geographically and institutionally, we conducted country- and institution-level analyses of productivity.

3.4 Thematic analysis, ethical considerations and reliability

Building upon the performance-based analyses, the intellectual and conceptual frameworks of the field were scrutinised using network- and content-oriented methodologies. Co-citation and bibliographic coupling analyses were utilised to uncover shared epistemic foundations and coherent research clusters. To ascertain the substantive focus of this body of scholarship, keyword co-occurrence analysis and text mining of titles and abstracts were carried out, facilitating the identification of dominant and emerging themes. Lastly, thematic evolution analysis was employed to trace conceptual shifts over time, emphasising the transition from traditional WIL models to AI-supported mentoring, virtual internships, and digitally mediated workplace learning.

As the study relied exclusively on publicly available secondary bibliographic data, formal ethical clearance was not required. Nonetheless, the study adhered to established ethical research norms, including the responsible utilisation of publicly accessible data and the accurate citation of sources. The reliability of the findings was enhanced through transparent search strategies, reproducible analytical procedures, and triangulation across multiple bibliometric techniques and software tools

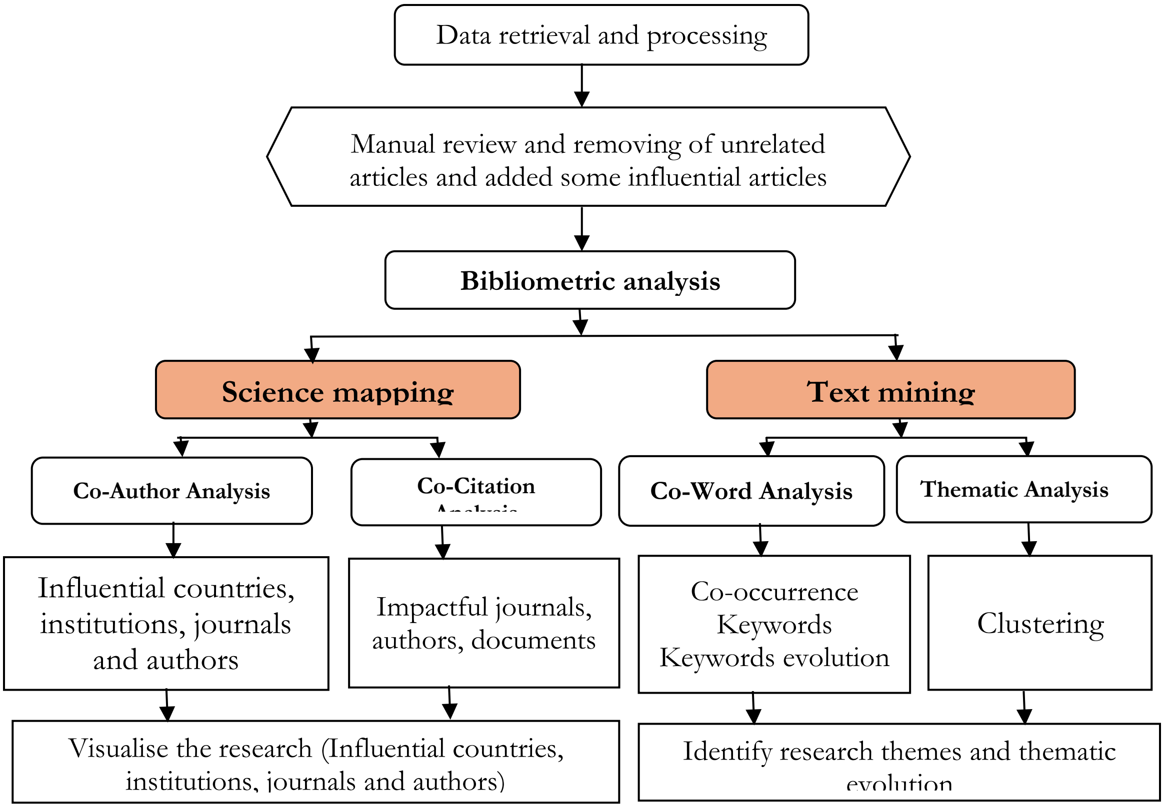

Figure 1: *Methodology flow*

4. Data analysis and interpretations

Table 3 summarises key data extracted from the WoS database between 2015 and 2025.

Table 3: *Key information of WIL scholarship*

Description	Results
Main information about the data	
Timespan	2015:2025
Sources (Journals)	529
Documents	4995
Annual Growth Rate %	-12.51
Document Average Age	3.13
Average citations per doc	10.84
Document contents	
Author's Keywords (DE)	13628
Authors	
Authors	14499

Authors of single-authored docs	714
Authors collaboration	
Single-authored docs	772
Co-Authors per Doc	3.36
International co-authorships %	19.94
Document types	
Article	4975

4.1 Acceleration and consolidation of WIL scholarship in AI-driven contexts

Year-on-year (YoY) growth in publications and citations was analysed to map the field's non-linear evolution. The formative phase (2015-2019) showed volatile publication growth alongside rapid citation expansion, providing evidence of early knowledge consolidation. A 234.9% surge in publications in 2020 marked a structural inflexion, shifting the field from exploration to large-scale expansion amid widespread AI adoption. The convergence of publication and citation growth rates after 2021 may suggest increasing consensus around methodological approaches, although this inference requires further qualitative validation. The recent phase (2024-2025) displays exponential growth in both metrics, reflecting mainstreaming and algorithmically amplified visibility. For WIL, this signals a shift from descriptive employability models towards AI-mediated, data-informed, and skills-adaptive frameworks. Impact now seems to depend on integrating learning analytics, automation, and workplace intelligence to align curricula with fast-changing labour market needs.

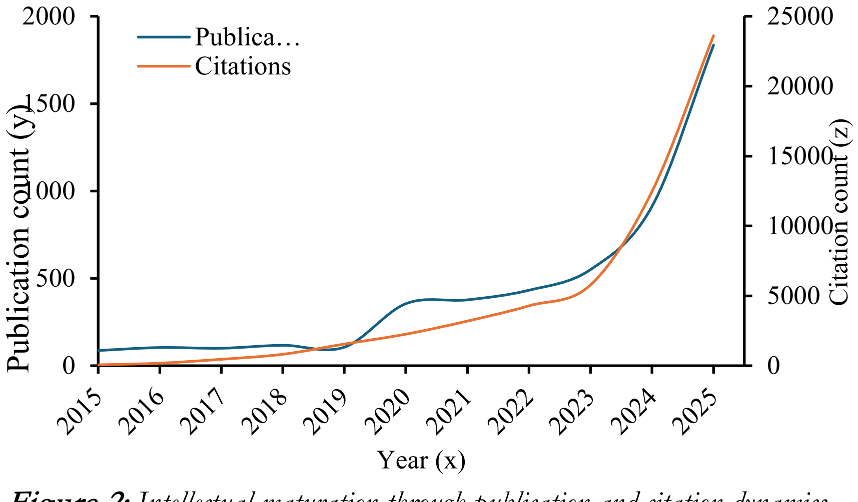

Figure 2: *Intellectual maturation through publication and citation dynamics*

4.1.1 Publications and citations growth

The annual number of publications grew from 87 in 2015 to a peak of 1,835 in 2025, with an average of 414.58 publications per year. As presented in Table 3, this represents a consistent upward trajectory over the study period. The year-on-year percentage growth rates for both publications and citations were calculated using the following formula:

(Current-Previous)/Previous × 100)

The YoY growth rate measures how much the number of publications has increased or decreased compared to the previous year, expressed as a percentage. This growth rate is determined by calculating the percentage change in publication output from one year to the next, thereby capturing increases or declines in research productivity over time.

Table 4: *YoY Growth of publications*

Year	Publication count	Publication Growth (%)	Citation count	Citation Growth (%)
2015	87	–	62	–
2016	104	19.54	181	191.94
2017	100	−3.85	459	153.59
2018	117	17.00	819	78.43
2019	106	−9.40	1550	89.26
2020	355	234.91	2257	45.61
2021	377	6.20	3194	41.52
2022	432	14.59	4286	34.18
2023	550	27.31	5779	34.83
2024	912	65.82	12465	115.69
2025	1835	101.21	23609	89.43

4.2 Global patterns of productivity and scholarly influence in WIL

Among these, the United States, China, and Australia emerged as the most prolific contributors (see Table 6). The resulting geographic concentration is visually underscored in Figure 3, which illustrates that global scholarship is predominantly characterised by research outputs from the United States, China, and Australia. This phenomenon underscores how WIL knowledge production remains entrenched within a limited number of highly resourced higher education systems. Such unipolarity raises significant questions regarding whose contexts, labour markets, and pedagogical models are influencing the global WIL discourse.

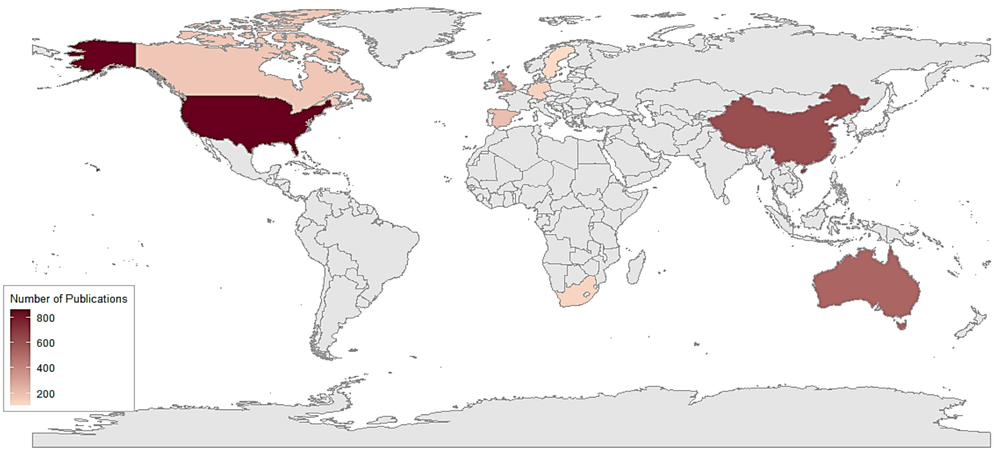

Figure 3: *Geographies of knowledge production in the field*

To isolate significant contributors and ensure analytical robustness, we applied a strict inclusion criterion with a dual threshold of a minimum of 10 documents and 100 citations for a country to be included in the final analysis. This criterion reduced the dataset from 125 countries to 60 eligible nations. The bibliometric network analysis (Figure 4) reveals a distinct geopolitical concentration in WIL-AI research. The visualisation identifies three dominant clusters: a North America-Oceania hub (USA, Canada, Australia, New Zealand), a European Union bloc, and an East Asia-Pacific group led by China. This tripartite structure suggests that a substantial portion of the foundational knowledge, tools, and models for AI in WIL is currently generated in high-resource, technologically advanced economies. The pronounced underrepresentation of most Global South nations underscores a critical research-capacity gap. Within the field, this geographic imbalance raises the risk that emerging AI-WIL frameworks may be contextually narrow, potentially misaligned with the socioeconomic realities and labour markets of underrepresented regions, and may inadvertently perpetuate rather than mitigate global skills inequalities.

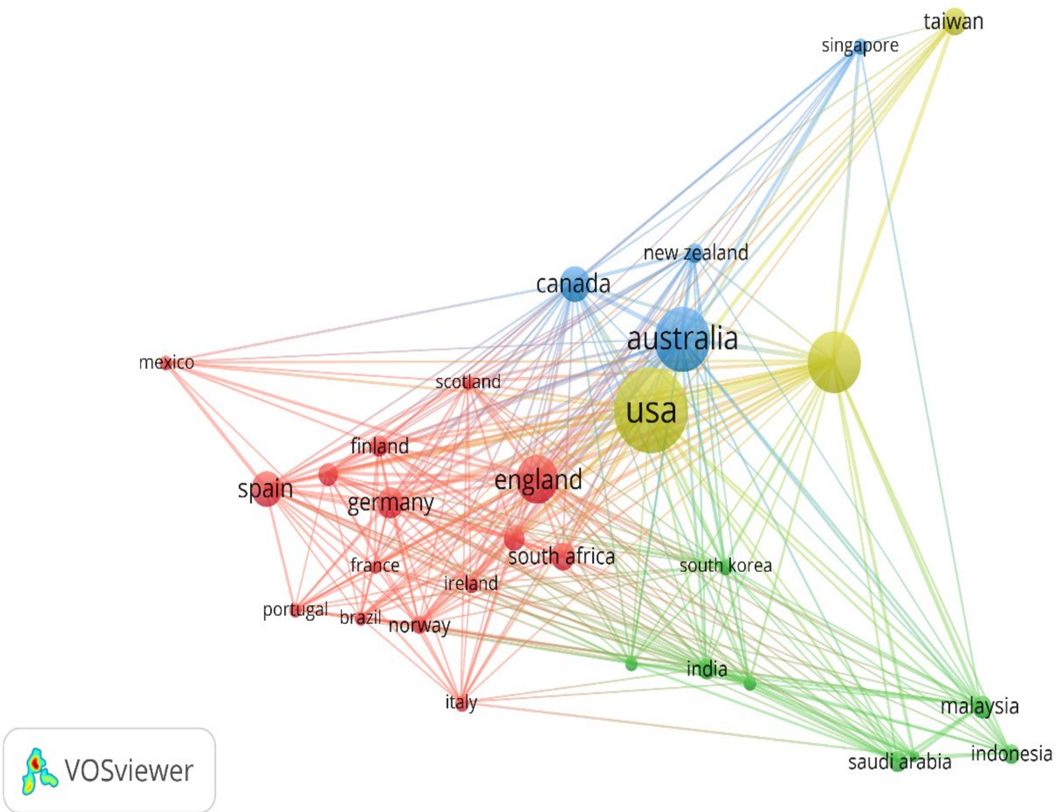

Figure 4: *Countries' productivity impact*

Table 5. *National and regional leadership in WIL knowledge production (Top 20)*

		2015-2025							2015-2017		2018-2019		2020-2021		2022-2023		2024-2025	
No	Country	TP	TP %	TC	C/P	SCP	MCP	MCP %	TP	TC	TP	TC	TP	TC	TP	TC	TP	TC
1	USA	860	17.2	8648	10.10	777	83	9.7	81	2586	85	1852	186	2376	200	2079	442	1561
2	China	614	12.3	8201	13.40	487	127	20.7	11	342	13	261	33	906	89	3889	422	1969
3	Australia	528	10.6	7847	14.90	422	106	20.1	53	2191	47	1647	145	2105	141	1679	224	950
4	United Kingdom	315	6.3	5127	16.30	242	73	23.2	28	1266	37	1434	72	1028	78	2333	164	1000
5	Spain	199	4	2126	10.70	166	33	16.6	15	618	14	941	31	696	62	502	117	391
6	Canada	171	3.4	1188	6.90	155	16	9.4	14	423	13	228	60	698	46	218	102	304
7	Germany	138	2.8	1585	11.50	102	36	26.1	9	387	-	-	29	469	35	587	94	403
8	South Africa	127	2.5	821	6.50	109	18	14.2	9	116	-	-	29	234	42	438	70	186
9	Sweden	102	2	1120	11.00	88	14	13.7	6	156	-	-	19	380	33	355	61	221
10	India	80	1.6	761	9.50	69	11	13.8	-	-	-	-	6	376	13	190	79	544
11	Netherlands	76	1.5	1726	22.70	55	21	27.6	22	610	-	-	29	543	18	828	42	199
12	Malaysia	74	1.5	545	7.40	45	29	39.2	-	-	-	-	-	-	11	122	78	363
13	Finland	71	1.4	1044	14.70	52	19	26.8	7	348	10	1434	13	167	18	358	47	281
14	Indonesia	70	1.4	165	2.40	55	15	21.4	-	-	-	-	-	-	-	-	70	165
15	New Zealand	65	1.3	850	13.10	47	18	27.7	7	435	-	-	28	355	17	163	36	278
16	Norway	60	1.2	480	8.00	40	20	33.3	-	-	-	-	20	223	-	-	-	-
17	Saudi Arabia	60	1.2	508	8.50	48	12	20	-	-	-	-	7	100	7	116	76	472
18	Israel	54	1.1	436	8.10	51	3	5.6	-	-	-	-	-	-	-	-	-	-
19	Ireland	50	1	309	6.20	36	14	28	-	-	-	-	11	103	-	-	-	-
20	Thailand	48	1	255	4.70	40	8	16.7	-	-	-	-	-	-	12	102	-	-

Abbreviations: R: rank; TP: total publications; TP%: percentage of publications; TC: total citations; C/P: citations per publication; SCP: Single-Country Publications, 'domestic' papers with no international collaboration; MCP: Multiple-Country Publications, the number of publications produced through international cooperation; MCP%: Multiple-Country Publications Percentage.

4.3 Institutional concentration and its implications for field development

The institutional analysis refined the dataset from 4,059 institutions to 69 significant contributors that met the threshold of 15 documents and 100 citations (the top 20 in Table 7). The threshold of at least 15 documents and 100 citations was applied to focus the analysis on institutions with sustained productivity and meaningful impact, thereby enhancing the robustness and interpretability of the results. The dominance of Australian institutions in the top tier of WIL research, as evidenced by four leading positions (Table 7), can be attributed to a confluence of national policy, systemic investment, and academic-cultural prioritisation. Australia has enacted a sustained, nationwide strategy that integrates WIL as a core component of higher education policy and funding frameworks (Jackson & Cook, 2025). This approach is supported by cohesive university-industry partnerships and dedicated research centres that regard WIL not as an ancillary activity but as a primary scholarly domain. The prominence of Australian institutions suggests that WIL research may be influenced by deliberate and coordinated national efforts. The integration of WIL into higher education policy and funding frameworks appears to incentivise and support universities in embedding WIL within curricula and advancing related research. Consequently, Australian institutions are better positioned to produce sustained, high-quality, and well-funded WIL scholarship, which can enhance their visibility and citation impact. More broadly, this pattern indicates the potential for systemic policy alignment and strategic investment to shape not only educational practice but also the global research landscape within the field.

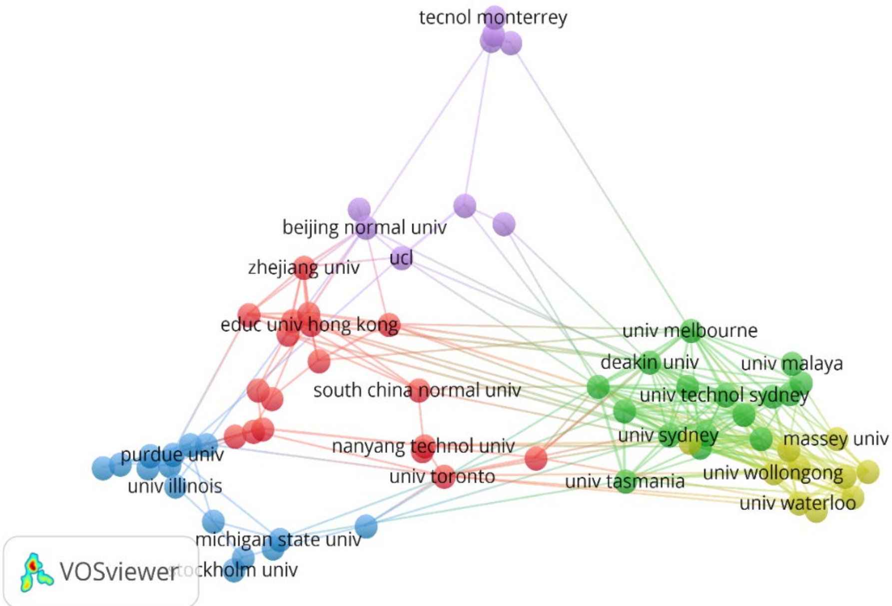

***Figure 5**: Institution productivity visualisation*

The institutional network (Figure 5) reveals a specialised leadership structure. Dominance is held by applied educational technology institutions, such as the Tecnológico de Monterrey (Mexico), a Chinese cohort led by Beijing Normal and Zhejiang Universities, and a dense cluster in Australia. Traditional U.S. and European education research centres are minimally represented. This indicates that the field is shaped by regionally concentrated, practice-driven innovation, which risks creating fragmented theoretical foundations and a growing divide between technological application and core pedagogical research.

Table 6: *Centres of Excellence and Knowledge Leadership in WIL Research (Top 20)*

R	Institution	Country	TP	TC	C/P	ARWU	QS
1	University of Wollongong	Australia	56	650	11,61	301-400	184
2	Deakin University	Australia	55	1193	21,69	201-300	207
3	Edith Cowan University	Australia	50	1716	34,32	801-900	487
4	University of Sydney	Australia	50	700	14,00	72	20
5	Education University of Hong Kong	Hong Kong	46	441	9,59	801-900	-
6	Monash University	Australia	46	969	21,07	76	36
7	University of Hong Kong	Hong Kong	43	1946	45,26	67	11
8	Griffith University	Australia	40	779	19,48	301-400	268
9	University of Melbourne	Australia	40	302	7,55	38	19
10	University of Waterloo	Canada	40	351	8,78	151-200	119
11	Chinese University of Hong Kong	Hong Kong	37	1286	34,76	101-250	32
12	University of Queensland	Australia	36	427	11,86	65	42
13	Tecnológico de Monterrey	Mexico	35	608	17,37	-	187
14	University of Technology Sydney	Australia	35	1068	30,51	201-300	96
15	University of Toronto	Canada	35	389	11,11	25	29
16	Beijing Normal University	China	34	301	8,85	101-150	247
17	Curtin University	Australia	33	345	10,45	201-300	183
18	Purdue University	USA	32	469	14,66	101-150	88

19	RMIT University	Australia	32	235	7,34	301-400	125
20	Nanyang Technological University	Singapore	30	389	12,97	88	12

The 2025 Academic Ranking of World Universities https://www.shanghairanking.com/rankings/arwu/2025; QS: World University Rankings 2026 https://www.qschina.cn/en/university-rankings/world-university-rankings/2026

4.4 Journals defining scholarly conversation and trajectory

Out of 579 journals, 77 met the threshold of at least 10 publications and 100 citations per journal, representing a balance of productivity and scholarly influence. Table 8 presents the top 20 ranked journals based on publication output and citation impact. Prominent journals (Figure 6), such as Education and Information Technologies, Education Sciences, International Journal of Work-Integrated Learning, Frontiers in Education, and Higher Education Skills and Work-Based Learning, exhibit widespread readership and robust citation networks. Scholars publishing in these journals not only enhance their visibility but also amplify their potential for impact, collaboration, and engagement in ongoing dialogues within the realms of education and WIL research. These journals are considered benchmarks for both academic rigour and strategic publication strategies.

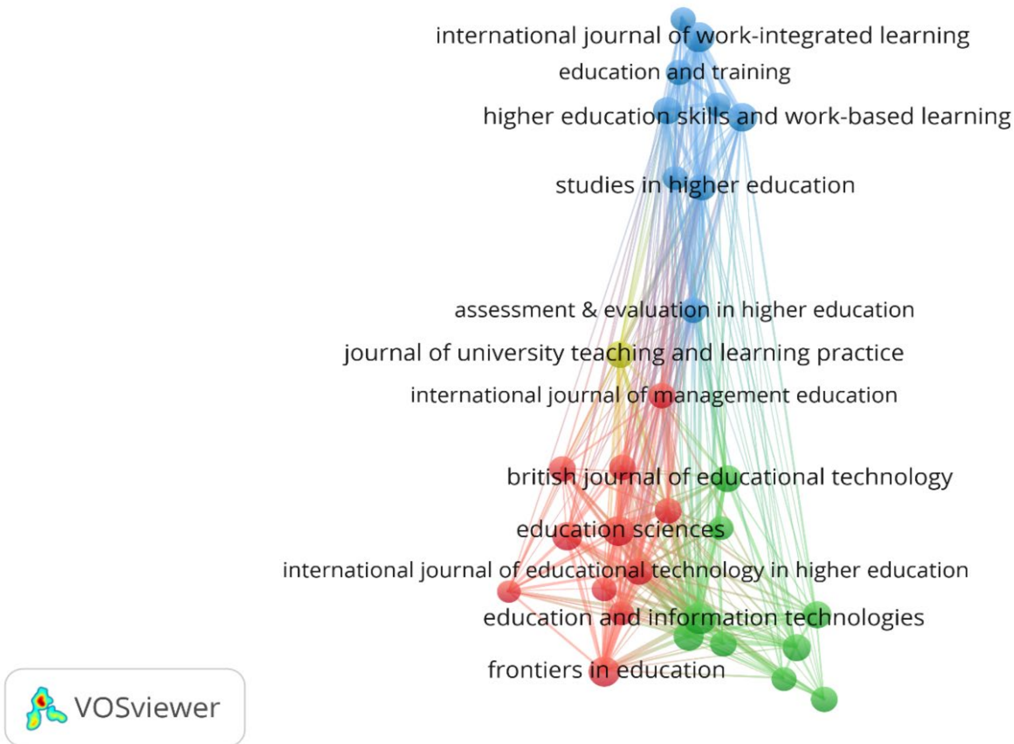

Figure 6: *Journal citation network visualisation*

Table 7: *Elite Journals and the Circulation of High-Impact WIL Research (Top 20)*

	Source	TP	TC	C/P	H index	G index	M index	IF (Q) 2024	5-Year IF
1	Education and Information Technologies	232	3491	15.05	31	50	3.44	5.4 (1)	5.7
2	Education Sciences	216	1849	8.56	20	36	2.86	2.6 (1)	2.7
3	International Journal of Work-Integrated Learning	195	992	5.09	14	21	2.00	1.5 (2)	2.1
4	Frontiers In Education	158	647	4.09	14	20	2.00	1.9 (2)	2.4
5	Higher Education Skills and Work-Based Learning	105	455	4.33	10	16	1.43	1.8 (2)	2.1
6	Cogent Education	95	464	4.88	11	20	2.20	2.0 (2)	2.1
7	Interactive Learning Environments	90	2135	23.72	20	45	1.67	5.3 (1)	6.2
8	British Journal of Educational Technology	65	1173	18.05	19	32	1.58	8.1 (1)	8.1
9	Studies In Higher Education	58	1830	31.55	22	42	1.83	3.2 (1)	4.7
10	Higher Education Research & Development	57	649	11.39	14	23	1.17	2.9 (1)	3.7
11	Journal of University Teaching and Learning Practice	57	1094	19.19	12	32	1.71	4.4 (1)	3.1
12	Social Work Education	57	270	4.74	9	14	1.29	1.1 (1)	1.6
13	Computers & Education	56	2576	46.00	28	50	2.33	10.5 (1)	13
14	International Journal of Educational Technology in Higher Education	50	3130	62.60	22	50	2.00	16.7 (1)	15.5
15	Journal of Computer Assisted Learning	48	514	10.71	13	21	1.08	4.6 (1)	5.9
16	European Journal of Education	47	316	6.72	9	17	0.82	3.6 (1)	4.0
17	Ieee Transactions on	46	414	9.00	11	19	1.10	4.9 (1)	5.5

18	Learning Technologies International Journal of Management Education	41	918	22.39	14	30	1.56	7.4 (1)	7.2
19	Educational Technology Research and Development	41	548	13.37	13	23	1.08	4.2 (1)	5.3
20	Journal of Social Work Education	40	322	8.05	11	16	0.92	1.2 (2)	1.5

Abbreviations in Table 7, H-index: A journal has an h-index of h if they have h publications each cited at least h times; G-index: A journal has a g-index of g if their top g publications together have at least g² citations; M-index: Normalises the h-index by career length. IF (Q) 2025 = 2025 Impact Factor, with quartile ranking (Q1–Q4) in the subject category; 5-Year IF = 5-Year Impact Factor, averaging citations over the previous five years.

4.5 Pillars of knowledge production

Of the 14,499 authors, 59 fulfilled the criteria of having a minimum of five publications and 20 citations, with 21 forming discernible collaborative networks (Figure 7). In accordance with bibliometric conventions for recognising prolific contributors, authors were assessed based on their productivity, citation counts, and h-index (Table 11). Leading scholars, including Jackson, D., Boud, D., and Chai Ching, S., are distinguished by the significant influence of their work across multiple subfields. Their research has shaped key debates and garnered extensive citations, thereby consolidating their central role within the scholarly community. For emerging researchers, engaging with the work of these authors or collaborating within their networks presents strategic opportunities to enhance visibility and increase impact.

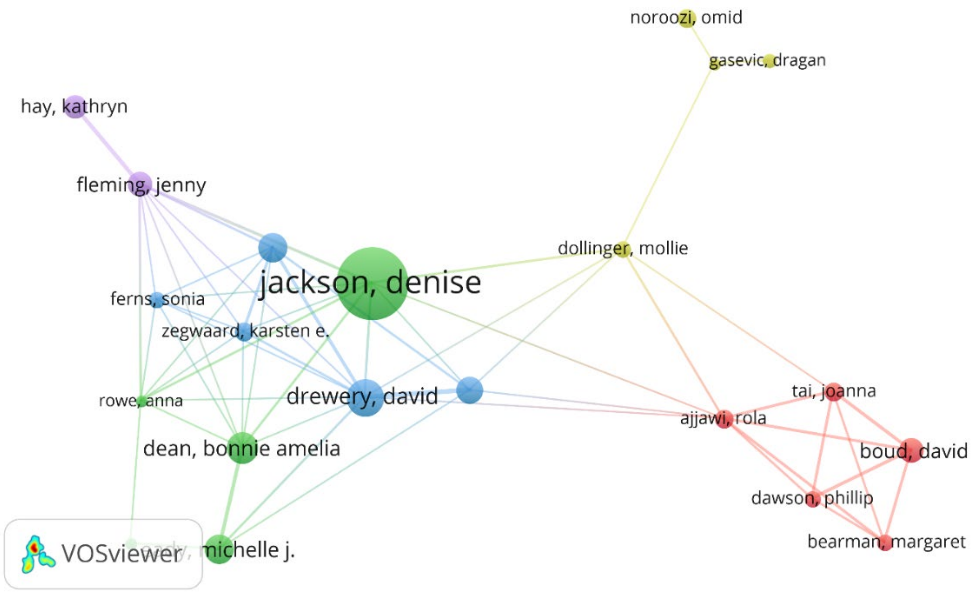

Figure 7: Network visualisation of authors

Table 8: *Elite authorship of WIL scholarship (Top 20)*

R	Author(s)	Profile/author page (direct link)	H Index	G index	M Index	TP	TC	PY start
1	Jackson, D	https://scholar.google.com/citations?hl=en&user=24GmN7IAAAAJ&utm_	19	35	1.58	35	1690	2015
2	Boud, D	https://scholar.google.com/citations?hl=en&user=nwO_6ukAAAAJ&utm_	8	11	0.89	11	697	2018
3	Chai C, S	https://scholar.google.com/citations?user=UFPLt7AAAAAJ&hl=en&oi=ao	8	10	0.80	10	737	2017
4	Pretti, J	https://scholar.google.com/citations?user=65ANDDwAAAAJ&hl=en&oi=ao	8	13	1.00	13	192	2019
5	Chiu, T	https://scholar.google.com/citations?user=waxoip4AAAAJ&hl=en&oi=ao	7	13	1.40	13	968	2022
6	Hwang, GJ	https://scholar.google.com/citations?user=H0wG-t4AAAAJ&hl=en&oi=ao	7	16	0.64	19	284	2016
7	Roberts, C	https://scholar.google.com/citations?user=KWVND8YAAAAJ&hl=en&oi	7	8	0.64	8	278	2016
8	Bozkurt, A	https://scholar.google.com/citations?user=8HKKXGUAAAAJ&hl=en&oi=ao	6	8	1.20	8	143	2022
9	Chan C, KY	https://scholar.google.com/citations?user=0wkKzzgAAAAJ&hl=en&oi=ao	6	7	1.50	7	1526	2023
10	Dean, B	https://scholar.google.com/citations?user=V8epkZwAAAAJ&hl=en&oi=ao	6	13	0.86	14	172	2020
11	Fleming, J	https://scholar.google.com/citations?user=VI-7H-oAAAAJ&hl=en&oi=ao	6	11	0.75	11	146	2019
12	Strzelecki, A	https://scholar.google.com/citations?user=_YLW4XwAAAAJ&hl=en&oi=ao	6	9	2.00	9	738	2024
13	Tai, J	https://scholar.google.com/citations?user=ilfMvcsAAAAJ&hl=en&oi=ao	6	8	0.67	8	638	2018
14	Ajjawi, R	https://scholar.google.com/citations?user=uFaXeLYAAAAJ&hl=en&oi=ao	5	8	0.56	8	703	2018
15	Cukurova, M	https://scholar.google.com/citations?user=OsfFt0cAAAAJ&hl=en&oi=ao	5	6	1.25	6	76	2023
16	Dawson, P	https://scholar.google.com/citations?user=0LcJrnsAAAAJ&hl=en&oi=ao	5	7	0.56	7	517	2018
17	Eady, M	https://scholar.google.com/citations?user=QDOHSj4AAAAJ&hl=en&oi=ao	5	6	0.71	13	55	2020
18	Hay, K	https://scholar.google.com/citations?user=EJJPP7IAAAAJ&hl=en&oi=ao	5	8	0.71	10	72	2020
19	Kim, J	https://scholar.google.com/citations?user=9SuiJiwAAAAJ&hl=en&oi=ao	5	6	1.67	6	131	2024
20	Morphet, J	https://scholar.google.com/citations?user=pGy3brkAAAAJ&hl=en&oi=ao	5	5	0.71	5	94	2020

Abbreviations in Table 1, except PY Start (Publication Year Start): The year a given document was published.

4.5 Seminal works setting the research agenda

We examined WIL publications that met a threshold of at least 100 citations per article to capture the field's most highly cited contributions as a proxy for influence. Out of 4,995 documents, 70 met this criterion, highlighting a select set of highly impactful studies. The citation network (Figure 8) and the top 20 cited works (Table 12) underscore the impact of authors such as Cotton, Dre (2024), Chan, Cky (2023), and Farrokhnia, M (2024), whose research has shaped WIL scholarship. For scholars, these works represent critical reference points and offer both a roadmap for high-impact research and potential avenues for collaboration or further investigation in the field.

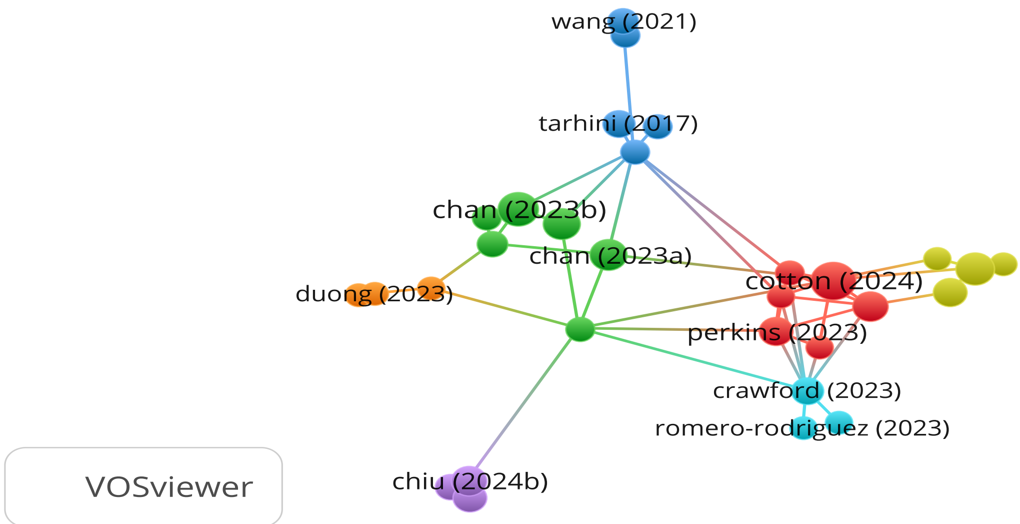

Figure 8: *Document citation network analysis*

Table 1: *High-impact publications structuring the WIL knowledge base (Top 20)*

R	Paper	DOI	TC	C/Y	Normalised TC
1	Cotton Dre, 2024	https://doi.org/10.1080/14703297.2023.2190148	1181	393.67	97.43
2	Chan Cky, 2023	https://doi.org/10.1186/s41239-023-00411-8	718	179.50	45.89
3	Farrokhnia M, 2024	https://doi.org/10.1080/14703297.2023.2195846	582	194.00	48.01
4	Crompton H, 2023	https://doi.org/10.1186/s41239-023-00392-8	482	120.50	30.80
5	Chan Cky, 2023	https://doi.org/10.1186/s41239-023-00408-3	466	116.50	29.78
6	Jackson D, 2015	https://doi.org/10.1080/03075079.2013.842221	452	37.67	14.58
7	Tai J, 2018	https://doi.org/10.1007/s10734-017-0220-3	419	46.56	15.26
8	Strzelecki A, 2024	https://doi.org/10.1080/10494820.2023.2209881	366	122.00	30.19
9	Greenhow C, 2016	https://doi.org/10.1080/17439884.2015.1064954	358	32.55	11.10
10	Chiu Tkf, 2024	https://doi.org/10.1080/10494820.2023.2253861	348	116.00	28.71
11	Perkins M, 2023	https://doi.org/10.53761/1.20.02.07	313	78.25	20.00
12	Chatterjee S, 2020	https://doi.org/10.1007/s10639-020-10159-7	303	43.29	17.20

13	Michel-Villarreal R, 2023	https://doi.org/10.3390/educsci13090856	299	74.75	19.11
14	Chiu Tkf, 2024	https://doi.org/10.1080/10494820.2023.2172044	276	92.00	22.77
15	Manca S, 2016	https://doi.org/10.1016/j.compedu.2016.01.012	276	25.09	8.56
16	Tarhini A, 2017	https://doi.org/10.1080/10494820.2015.1122635	249	24.90	7.50
17	Mohammadyari S, 2015	https://doi.org/10.1016/j.compedu.2014.10.025	249	20.75	8.03
18	Crawford J, 2023	https://doi.org/10.53761/1.20.3.02	244	61.00	15.59
19	Xia Q, 2022	https://doi.org/10.1016/j.compedu.2022.104582	211	42.20	19.45
20	Jackson D, 2017	https://doi.org/10.1007/s10734-016-0080-2	193	19.30	5.81

4.6 Core topics and emerging research themes

4.6.1 Keywords analysis

Keywords in an article serve as the conceptual anchors of the research, and their frequency and co-occurrence not only illuminate dominant topics but also reflect the intellectual priorities that shape the field (Radhakrishnan et al., 2017). Among the 13,628 keywords extracted from the dataset, only 84 met the minimum threshold of 50 occurrences, indicating a highly consolidated thematic structure. As illustrated in Figure 9, the research is firmly centred on artificial intelligence, education, and higher education, with an increasing prominence of terms such as "students," "ChatGPT," "generative AI," "technology," and "employability." This pattern signifies a shift from traditional Work Integrated Learning (WIL) conceptualisations towards an emerging focus grounded in artificial intelligence.

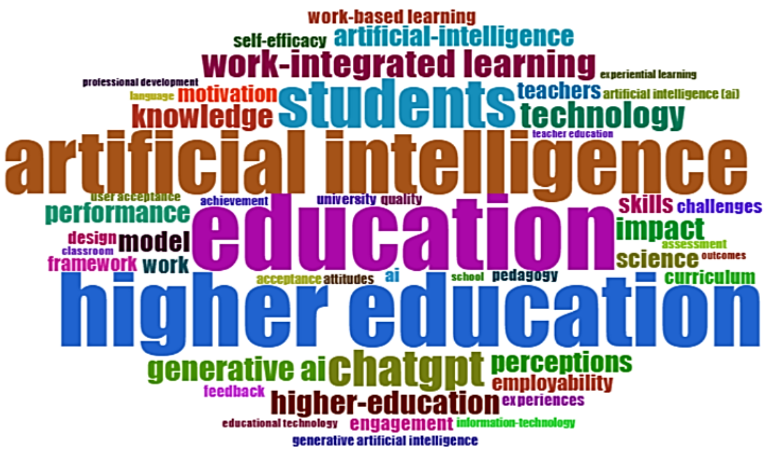

Figure 8: Frequency word cloud

4.6.2 What Are the current and future WIL thematic directions?

Triangulating the keyword co-occurrence overlay network (Figure 10) with the thematic evolution map (Figure 11) provides convergent evidence of a substantial reorientation of WIL scholarship towards AI-mediated forms of WIL. The dense green cluster (Figure 10), anchored in education, skills, performance, and employability, reflects the field's traditional concern with learning outcomes and graduate readiness. In contrast, the emergent yellow cluster, centred on artificial intelligence, generative AI, and ChatGPT, signals a rapid shift towards technologically mediated forms of WIL. Crucially, the strong connective ties between these clusters, via constructs such as self-efficacy, technology, feedback, and user acceptance, suggest that employability is increasingly produced through sociomaterial assemblages in which human capability and intelligent systems are co-constitutive.

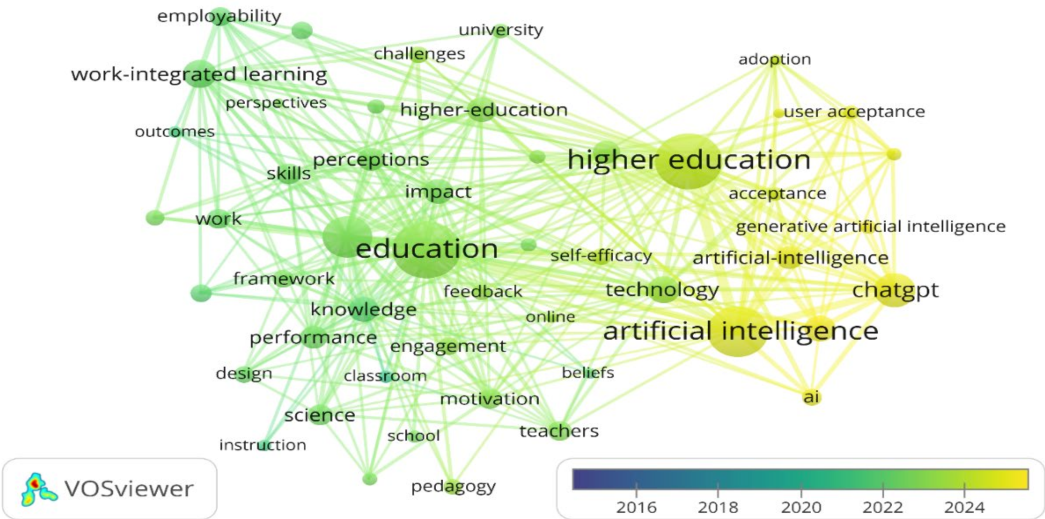

Figure 9: *Keyword co-occurrence overlay network*

The thematic evolution analysis (Figure 11) indicates a clear longitudinal shift in WIL scholarship. Between 2015 and 2018, research focused on foundational educational concerns, including work-based learning, students, teachers, and knowledge. During 2019-2020, WIL emerged as a consolidated construct, accompanied by themes of reflection, collaboration, and pedagogical models, signalling an increasing conceptual formalisation. In 2021-2022, attention shifted toward outcome-oriented themes such as impact, while maintaining continuity around education and students. From 2023 onwards, the literature exhibits a marked inflection towards technology-mediated learning, with the emergence of motivation, self-regulated learning, and generative learning. Although the study period spans 2015-2025, thematic evolution beyond 2025 is expected to be increasingly shaped by AI-related themes. In particular, higher-order competencies such as critical thinking and strategic behaviour are likely to become more prominent, suggesting a reorientation of WIL towards AI-mediated environments.

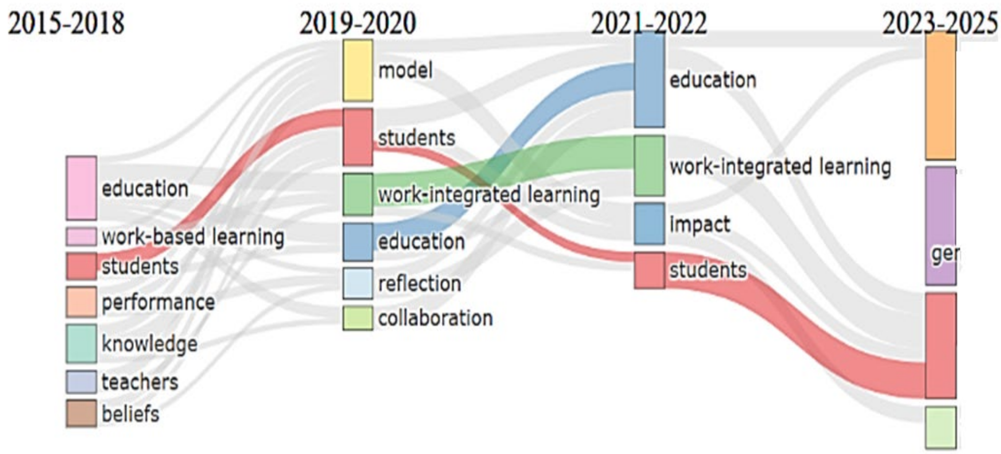

Figure 10: Thematic evolution analysis

5. Discussion

This chapter presents a comprehensive bibliometric analysis of WIL scholarship in the AI-driven era from 2015 to 2025. By integrating quantitative bibliometrics with interpretive thematic evolution tracking, this chapter transcends the descriptive trends that characterise much of the existing review literature. The findings reveal not only the accelerating volume and shifting geography of research but, more importantly, the profound intellectual reconfiguration of WIL as it responds to the pressures and possibilities of AI. This discussion contextualises these findings within the existing body of bibliometric reviews on WIL, highlighting points of convergence and contradiction, and, most critically, the novel contributions this analysis makes to understanding a field in transition.

5.1 Accelerated and inflected growth: Confirming and extending trajectories

Prior bibliometric studies of WIL have consistently documented steady growth, attributing it to the global emphasis on graduate employability and experiential education. For instance, Rafiq et al. (2024) noted rapid growth post-2015, while Amarathunga et al. (2024) and Bezerra et al. (2021) mapped a consistent upward trajectory in publication output. This chapter confirms that overarching trend but introduces a crucial nuance. This nuance is the identification of a structural inflexion point around 2020, characterised by a 234.9% year-on-year surge in publications. This discontinuity, not explicitly highlighted in earlier reviews, aligns with the catalytic convergence of the COVID-19 pandemic's impetus towards digitalisation and the maturation of accessible artificial intelligence tools, such as advanced learning analytics and generative AI. This suggests that, in contrast to the more linear narratives of past studies, AI has functioned less as an incremental topic of interest and more as a disruptive catalyst, compressing and accelerating the field's development. Furthermore, while Gessler et al. (2021) analysed trends up to 2020 and noted a growing interest, our extended timeline to 2025 captures the subsequent phase of 'rapid growth,' indicating the field's swift transition from an emerging niche to a mainstream, interdisciplinary research frontier.

5.2 Geographies of knowledge production: persistent imbalances and polycentricity

The geographic distribution of WIL research has been a consistent focus of prior bibliometric analyses, with a clear consensus regarding the predominance of Anglophone and Western European nations. Areskoug Josefsson et al. (2024), Winchester-Seeto and Rowe (2019), and Bezerra et al. (2021) all identified Australia, the UK, the USA, and Canada as the most prolific contributors. Our findings corroborate the sustained productivity of these nations, particularly highlighting Australia's notable institutional dominance. However, this study adds a significant dimension to this understanding by documenting the dramatic increase in East Asian scholarship, led by China, which now ranks second in both output and citation impact. This shift begins to address the calls made by Moosa & Shareefa (2020) for greater contributions from Eastern and Asian contexts, although our network analysis reveals that these contributions often form a distinct cluster. Crucially, this emerging polycentricity coexists with a persistent and pronounced underrepresentation of the Global South. This observation reinforces the critical limitations noted by Gessler et al. (2021), who cautioned that scholars from developing countries are frequently excluded from the international discourse. Our analysis extends this critique into the era of artificial intelligence and suggests the potential for a dangerous feedback loop. We caution that AI-WIL models are predominantly designed in and for high-resource, technologically intensive environments, potentially widening rather than bridging global inequities in skills development. This geographic imbalance moves beyond the descriptive 'who publishes' reported in earlier studies to highlight a fundamental contextual misalignment in the field's foundational knowledge, presenting a novel and critical implication for future research and policy.

5.3 Thematic evolution

Thematic analysis has been a component of previous reviews; however, such analyses have often remained at a high level or within a narrow scope. Ademuyiwa et al. (2024), for instance, identified equity and skills as predominant themes within a single journal, while Yoo et al. (2025) employed topic modelling to trace broad multidisciplinary growth. The longitudinal co-word and thematic evolution analysis offers a granular and dynamic perspective. It substantiates the foundational themes of 'employability,' 'reflection,' and 'pedagogical models,' which have been consistently reported in the literature, and maps their evolution over time. A key innovation in this analysis is the clear visualisation of a thematic pivot occurring post-2020, leading to the predominance of AI-centric terms such as 'generative AI,' 'ChatGPT,' and 'virtual internship' by 2025. Earlier reviews, even those published recently that relied on data concluding in 2023, were unable to fully capture this rapid reorientation. This shift signifies more than merely the introduction of new keywords; it represents an epistemic evolution in the conceptualisation of

WIL. The field is transitioning from a socio-cultural model—emphasising community, mentorship, and situated practice—towards a socio-technical paradigm where intelligent systems and data mediate learning. This development directly engages with the emerging scholarly inquiry noted in the introduction, concerning virtual internships, intelligent tutoring, and simulation-based training, and provides substantial bibliometric evidence that these are not marginal interests but rather central, defining trends.

5.4 Fragmentation, convergence, and a new interdisciplinary core

A recurring critique in the WIL narrative literature, and, indirectly, in bibliometric reviews, is the field's conceptual fragmentation across disciplinary silos. Our co-citation and bibliographic coupling analyses provide an empirical map of this structure. While fragmentation persists, we also identify the formation of a convergent interdisciplinary core. Influential scholars are no longer solely veteran WIL theorists (e.g., Jackson, Boud, Zegwaard). The field now actively incorporates leading voices from educational technology and artificial intelligence in education (e.g., Hwang, G.-J.; Chiu, T.K.F.). This fusion represents a pivotal development. Unlike the discipline-bound analyses lamented in the introduction, this convergence suggests the emergence of a transdisciplinary dialogue that is essential for addressing the complex challenges of AI-mediated WIL. Furthermore, our analysis of seminal works reveals that recent, high-impact studies are disproportionately focused on AI applications (e.g., Cotton, 2024; Chan, 2023; Farrokhnia, 2024). This indicates that technological innovation is increasingly shaping the research agenda, a dynamic not evident in earlier bibliometric snapshots that highlighted foundational WIL theory papers. This has implications for the field's theoretical development, potentially privileging applied, technology-focused studies over critical, philosophical, or socio-cultural explorations of work and learning.

6. Conclusions and Forward-Looking Implications

This chapter makes several distinct contributions that address gaps explicitly identified in prior reviews. First, it provides a large-scale, dedicated analysis of WIL in the AI-driven era, addressing the lack of coherent synthesis noted in the introduction. Second, it employs a methodologically triangulated approach, combining performance analysis, network science, and thematic evolution, which moves beyond the descriptive trends observed in studies such as Amarathunga (2024) and Rafiq et al. (2024) to reveal relational and intellectual structures. Third, it interprets bibliometric patterns as epistemic indicators, arguing that the data reflect a paradigm shift in the conception of WIL itself. The implications are substantial. For researchers, the findings necessitate a deliberate engagement with both learning science and AI ethics, moving beyond isolated case studies to develop robust theories for hybrid human-AI WIL. For institutions, the accelerated growth and thematic shift underline an urgent need to invest in digital WIL infrastructure, educator training in AI tools, and ethical frameworks for algorithmic assessment. For policymakers, the geographic imbalances necessitate targeted funding to support contextually relevant AI-WIL research in underrepresented regions, ensuring that the future of work-integrated learning does not become another vector of global inequality. Institutions should invest in teacher training programmes that focus on the pedagogical integration of AI tools in WIL contexts, rather than assuming technological proficiency alone. Ultimately, this review establishes that the AI-driven era is not a future scenario but a present reality actively reshaping WIL scholarship and practice. The task ahead is to ensure that as WIL becomes increasingly intelligent, it also remains profoundly human.

7. Limitations and Future Directions

While this review provides a comprehensive mapping of WIL research in AI-driven contexts, several limitations must be acknowledged. First, the analysis relies exclusively on the WoS database, which prioritises English-language, high-impact articles. This inevitably excludes significant non-English publications, conference proceedings, and grey literature. Consequently, the findings may be skewed towards dominant scholarly discourses and established research communities, potentially overlooking emerging, practice-oriented, or regionally grounded contributions that are not indexed in WoS. Second, the ethical complexities and subjective experiences of AI-mediated WIL remain outside the scope of this chapter. These limitations delineate clear pathways for future inquiry. Subsequent research should employ multidatabase reviews, incorporating Scopus, regional indexes, and grey literature sources to construct a more geographically and linguistically inclusive knowledge base. Furthermore, longitudinal and predictive studies could track the real-world implementation and efficacy of AI tools in WIL settings, assessing their impact on learning outcomes, professional identity, and graduate trajectories. Finally, dedicated research must address the contextual adaptation of AI-WIL models for underrepresented regions and sectors, ensuring that the development of the field promotes inclusive, equitable, and socially responsible futures of work and learning.

8. Declarations

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CHAPTER TWO

Bridging the Digital Divide: Equitable Access to AI-Enhanced Geographical Work Integrated Learning in Marginalised Landscapes

Tolulope Ayodeji Olatoye
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley, South Africa

Thulasizwe Fredrick Mkhize
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley, South Africa

Raymond Nkwenti Fru
Department of Human Science Teaching, Faculty of Education,
Sol Plaatje University, Kimberley, South Africa

Corresponding author: Tolulope Ayodeji Olatoye (tolulope.olatoye@spu.ac.za).

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Abstract: This chapter confronts the alluring promise of Artificial Intelligence (AI) in geographical Work-Integrated Learning (WIL) with the stark reality of its potential to perpetuate and deepen existing socio-spatial inequalities. It addresses the critical issue of how the integration of AI risks exacerbating the very disparities it claims to resolve. While AI purports to democratise access through virtual placements and sophisticated analytics, its implementation often assumes the presence of robust digital infrastructure and high AI literacy, thereby creating a new "geo-digital divide" for students in marginalised geographies, including rural, low-income, and Global South contexts. Through a systematic literature review of relevant academic scholarship, framed by a synthesis of Critical Digital Pedagogy and Spatial Justice theories, this chapter interrogates the normative assumptions underpinning "high-tech" WIL models. Findings reveal that AI tools can perpetuate epistemic injustice without deliberate intervention by marginalising local knowledge and reinforcing technological dependency. Conversely, the chapter identifies emergent, innovative strategies such as mobile-first hybrid placements, community-partnered projects employing participatory geospatial technologies, and embedded "critical AI literacy" modules that leverage appropriate technology to foster inclusive and contextually relevant geographical WIL. Thus, this study provides a robust, theoretically grounded framework for the equitable design of AI-enhanced geographical WIL. The chapter advocates for asset-based partnerships among educators and policymakers, the co-design of curricula with local communities, and a pedagogical reorientation that utilises AI to amplify, rather than replace, situated geographical understanding in order to empower spatial citizenship for all.

Keywords: WAI-enhanced learning, geo-digital divide, mobile-first hybrid placements, spatial justice, work-integrated learning.

1. Introduction

The contemporary geographical sciences are positioned at a transformative juncture, driven by the dual forces of Artificial Intelligence (AI) and the pedagogical imperative of Work-Integrated Learning (WIL) (Govender & Våland, 2021; Raghubar, 2021). This convergence promises to revolutionise the training of future geographers, planners, and spatial analysts, presenting unprecedented opportunities for sophisticated data analysis, predictive modelling, and immersive virtual field experiences. AI-enhanced geographical WIL, which involves the integration of AI tools such as machine learning, computer vision, and natural language processing into experiential, workplace-relevant geographical education, signals a future characterised by democratized expertise (Hutson, 2024; Aragani et al., 2025). In theory, it has the potential to transcend physical and financial barriers, granting students worldwide virtual access to global datasets, simulated environmental scenarios, and remote mentorship. Yet, this narrative of technological democratization masks a more insidious potential: the risk of constructing a new, deeply entrenched "geo-digital divide" that systematically excludes marginalised geographies from the very future it endeavours to create.

This chapter, therefore, interrogates the ostensibly neutral deployment of AI in geographical WIL, arguing that, without a deliberate and critical framework for equity, these technologies risk becoming instruments of epistemic and socio-spatial exclusion (Cegielski, 2023). Consequently, the integration of AI constitutes a profoundly geographical and political act (Simon, 2019), one that can either reinforce existing centre-periphery dynamics or be harnessed to promote a more pluralistic and just spatial citizenship (Rakuasa, 2023). Spatial citizenship refers to the capacity of individuals and groups to actively participate in societal decision-making by producing, utilising, and negotiating spatial information through geo-media such as maps, virtual globes, GIS, and the Geoweb (Assumpção et al., 2018). It embodies an educational and civic approach that combines geographic knowledge with citizenship rights, empowering individuals to appropriate space. This means they can critically analyse, influence, and change the meanings attached to their surroundings rather than merely accepting them. To navigate this complex landscape, it is essential to establish the core conceptual lexicon and theoretical orientation (Shin & Bednarz, 2019).

AI-Enhanced Geographical WIL is defined as an experiential pedagogical model in which students of geography and related spatial disciplines apply AI methodologies to address real-world problems in partnership with industry, government, or community stakeholders (Lane, 2025). This extends beyond the use of GIS software to include, for example, training convolutional neural networks to analyse satellite imagery for urban change detection or employing natural language processing to assess community sentiment from qualitative survey data (Liu et al., 2025).

The Geo-Digital Divide is understood as a multi-dimensional gap that includes several key aspects: Access, which refers to the physical and financial availability of necessary computational infrastructure and reliable, high-bandwidth connectivity; Capability, which encompasses the skills and critical literacies required to effectively and ethically use, critique, and shape AI tools; Outcomes, which highlight the systemic tendency of AI systems to generate inequitable results, often by encoding biases present in training data or favouring certain types of knowledge over others; and Marginalized Geographies, which pertain to regions—whether in the Global South, deindustrialised areas of the Global North, or remote rural locations—that are systematically underserved by digital infrastructure and excluded from the main pathways of technological innovation and capital (Sarkar et al., 2015; Ash et al., 2018).

This analysis is framed by a synthesis of two theoretical traditions: Critical Digital Pedagogy and Spatial Justice. This integrated framework requires us to question the power relations embedded in educational technology, challenging the assumption that "more technology" is inherently progressive. It asserts that the distribution of technological benefits is fundamentally a matter of justice. Furthermore, it necessitates a shift from a deficit model, which focuses on what marginalized communities lack, to an asset-based model that harnesses local knowledge and context through appropriate technological mediation.

The primary issue at hand is one of profound misalignment. The dominant paradigm for AI-enhanced WIL, largely conceived and refined in the resource-rich environments of the Global North, operates on a set of normative assumptions that are often untenable in marginalised contexts. These assumptions include the presumption of ubiquitous high-speed broadband, universal access to powerful computing resources, and a baseline level of AI literacy among both students and educators (Antoninis et al. 2023). When these unstated prerequisites are not met, AI tools do not bridge gaps; rather, they exacerbate them. Consequently, controversies are prevalent (Tuomi et al. 2023).

Firstly, there is the risk of epistemic injustice, wherein AI models trained on data from the Global North produce inaccurate or irrelevant results when applied to different socio-ecological contexts, thereby silencing local ways of knowing. Secondly, the push for "high-tech" WIL can create a form of technological dependency, where educational institutions in marginalised regions are pressured to adopt expensive, proprietary platforms that divert scarce resources from more foundational needs, locking them into cycles of perpetual upgrade (Ndaka et al. 2025). Thirdly, the focus on virtual placements, while addressing one problem of access, may inadvertently devalue embodied, place-based knowledge, which is a cornerstone of geographical understanding.

The central controversy, therefore, revolves around whether AI in WIL serves as a tool for empowerment or acts as a new vector for neo-colonial imposition, exacerbating the very inequities it claims to address. The discourse surrounding AI in education is predominantly shaped by the priorities and contexts of the Global North (Nost & Colven, 2022). Here, substantial public and private investment fuels a vision of "seamless" digital learning ecosystems, where cloud-based AI platforms, virtual reality field trips, and automated tutoring systems are becoming the norm. This prevailing narrative, while innovative, often treats technology as an a-contextual, plug-and-play solution (Pimenow et al., 2025).

The export of this model, whether through international educational partnerships, corporate software licensing, or development aid, frequently overlooks the infrastructural pluralism, diverse epistemologies, and distinct socio-economic challenges faced by marginalised regions. As a result, the global conversation is skewed, with models developed for cities like Cambridge, Zurich, or Palo Alto being presented as universal benchmarks, thereby rendering alternative, low-bandwidth, or community-centric approaches invisible or illegitimate (Pfotenhauer & Jasanoff, 2017).

1.1 Problem statement

The critical problem addressed in this chapter is the systemic risk that AI-enhanced geographical Work-Integrated Learning (WIL) may perpetuate and amplify existing socio-spatial inequalities by neglecting the specific infrastructural, epistemological, and pedagogical realities of marginalised geographies (Şanlı, 2025). The current trajectory, if left uncorrected, leads to a future where the capability to engage in cutting-edge geographical practice is dictated by one's postal code or national economy, thereby establishing a two-tiered system of geographical education and professional opportunity (Addie et al., 2020). This investigation reveals that the most promising pathways are not located in merely scaling down Northern models, but in pioneering alternative approaches. The study illustrates how mobile-first hybrid placements, community-partnered projects employing participatory geospatial technologies, and curricula infused with "critical AI literacy" can foster more resilient and contextually significant learning experiences. The ultimate contribution of this work is a shift in perspective from utilising AI to replace situated geographical understanding to leveraging it as a tool to amplify local voices, validate community knowledge, and empower a new generation of spatial citizens equipped to navigate an increasingly automated world.

The research question guiding this study is: *How can the integration of AI into geographical Work-Integrated Learning be reconceptualised and redesigned to bridge, rather than widen, the geo-digital divide for students in marginalised geographies?* To address this question, the chapter undertakes a systematic analysis of academic literature and documented case studies, framed by a critical digital and spatial justice perspective.

2. Theoretical Framework

This study's dual theoretical framework integrates Critical Digital Pedagogy (CDP) and Spatial Justice Theory (SJT) as complementary and mutually reinforcing perspectives. Given the study's primary focus on equitable access to AI-enhanced Geographical WIL in marginalised landscapes, CDP offers critical tools for interrogating the assumptions embedded in digital and AI-driven educational models, foregrounding issues of agency, inclusion, and epistemic justice in technology-mediated learning. Conversely, SJT situates these concerns within the spatial and structural conditions that produce and perpetuate marginalisation, emphasising how place, scale, and geography influence students' differential access to knowledge and opportunity. Collectively, these frameworks establish an integrated critical space wherein the politics of technology and the politics of space are understood as inseparable. This synthesis generates a novel analytical foundation for reimagining AI-enhanced Geographical WIL as a site of equitable participation, affirmation of local knowledge, and transformative spatial citizenship.

2.1 Critical digital pedagogy: Unmasking the hidden curriculum of AI

Critical Digital Pedagogy Theory (CDPT), emerging from the foundational work of Paulo Freire and critical theorists such as Ivan Illich, and advanced by contemporary scholars like Jesse Stommel and Sean Michael Morris,is an approach that applies the principles of traditional critical pedagogy to the digital realm to empower students, interrogate the role of technology, and promote equity in learning (Masood & Haque, 2021). This approach entails a critical examination of digital tools and content, fostering dialogue through online platforms, and developing digital literacy to aid students in navigating and challenging the digital landscape (Morris & Stommel, 2018). The theory is grounded in the work of educators like Paulo Freire and bell hooks and is concerned with the impact of technology on learners, educators, and the learning environment (Baroud & Dharamshi, 2020).

The core tenets relevant to this study include the following: The Problem of "Banking" Education in Digital Guise: CDPT critiques the "banking" model of education, in which students are viewed as passive receptacles for deposited knowledge. In the context of AI-enhanced Work Integrated Learning (WIL), this is evident when AI tools, such as pre-packaged proprietary software or algorithmic models with opaque decision-making processes, are presented as infallible black boxes. Students are trained to use these AI tools without being encouraged to question their underlying assumptions, data biases, or the corporate interests embedded within their code. This creates a form of digital paternalism that inhibits critical thought (Kakhkharova & Tuychieva, 2024).

Critical Digital Pedagogy Theory emphasises that students should function as active co-creators of their digital learning environments rather than as passive consumers. As Gutiérrez-Ujaque (2024) elucidates, this necessitates a fundamental pedagogical shift—moving away from the use of AI as a substitute for human judgement, such as automated grading of spatial analyses, and towards its deployment as a dialogic partner for critical inquiry. In the context of Geographical WIL, this implies that rather than uncritically accepting an AI's land cover classification as unquestioned truth, students are empowered to investigate potential misclassifications of informal settlements and to rectify them using locally gathered, ground-truthed data, thereby asserting their role as knowledge producers rather than mere recipients.

Equally central to CDPT is the imperative to demystify technology by exposing it as a human construct that can be interrogated, adapted, and repurposed. This principle constitutes the essence of critical AI literacy, a core component of the framework proposed in this study (Masood & Haque, 2021). In practice, this involves equipping students with the capacity to understand how training data influences algorithmic outcomes, to critically reflect on the environmental costs associated with large language models, and to explore open-source alternatives to dominant corporate AI platforms (Markham, 2019; Figaredo, 2020). Figure 1 illustrates the conceptual architecture of CDPT as it informs this framework.

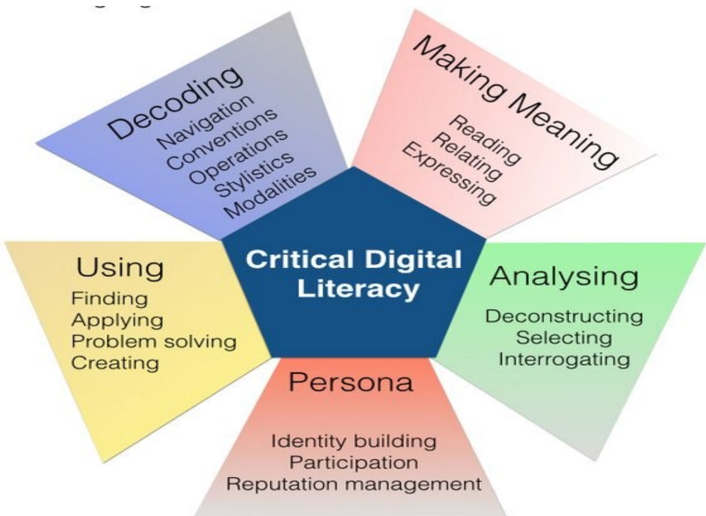

Figure 1: *The critical digital pedagogy theory (Walker, 2013)*

Figure 1 illustrates an existing model that informs the CDPT. This theory translates both CDPT and Social Justice Theory (SJT) from abstract principles into tangible competencies for equitable AI-enhanced Geographical WIL. Its foundational layers, Decoding and Making Meaning, are necessary but insufficient on their own, potentially resulting in a passive "banking" model of education. The higher-order domains of Using and Analysing foster student agency, enabling learners to interrogate algorithmic bias and co-create knowledge. Underpinning the entire framework is Critical Digital Literacy, which manages identity and participation within socio-technical systems. Collectively, these layers embed critical AI literacy into WIL, empowering students from marginalised geographies to interrogate, adapt, and repurpose tools designed in the Global North, rather than merely consuming them.

2.2 Spatial justice theory: The right to the digital-produced space

Spatial Justice, most prominently theorised by Edward Soja, builds upon Marxist and feminist geography to posit that justice is not solely a social construct but is intrinsically spatial. Fainstein (2016) contends that space is not a passive backdrop but rather an active, socially produced force that both shapes and is shaped by power relations, inequality, and social struggle. Spatial injustice arises when this production of space systematically favours certain groups while disadvantaging others (Riveros & Nyereyemhuka, 2023). The key principles guiding this analysis are: The Socio-Spatial Dialectic: This is the core concept that space and society are mutually constitutive (Halvorsen, 2017). The marginalisation of a geography (e.g., a rural community or an urban informal settlement) is both a cause and a consequence of its unequal access to resources, including digital infrastructure and educational opportunities. An AI-enhanced WIL programme that requires high-bandwidth connectivity does not merely overlook these areas; it actively reproduces their marginality by designing a system in which they cannot participate.

The Right to the City (and the Digital Sphere): Extending Henri Lefebvre's concept, Spatial Justice asserts a collective right to participate in the production of space. In the 21st century, this must include the right to participate in the production of digital space (Pierce, 2022). When AI tools used in WIL are trained exclusively on data from the Global North, they produce a digital representation of the world—a "code/space"—that is often illegible or hostile to the realities in the Global South. This constitutes a form of epistemic spatial injustice, whereby the knowledge and spatial experiences of the marginalised are erased or distorted (Riveros & Nyereyemhuka, 2023).

The Geography of Power and Visibility: Spatial Justice makes power relations visible by mapping their uneven geographical expression (Hafeznia & Ghaderi-Hajat, 2015). It prompts inquiries such as: Who benefits from this spatial arrangement? Who is rendered invisible? In our context, it compels us to ask: For whom is this AI tool designed? Whose knowledge does it valorise, and whose does it render obsolete? Figure 2 depicts the Spatial Justice Theory (SJT).

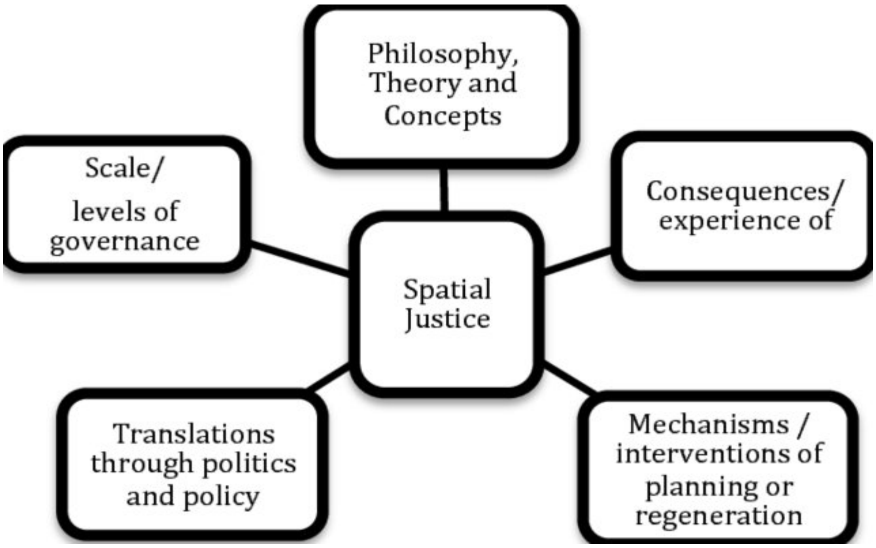

Figure 2: *The spatial justice theory (Scott, 2015)*

Figure 2 presents an established model that informs Spatial Justice Theory, framing its operationalisation as a multi-scalar process, thereby providing a structural blueprint for bridging the geo-digital divide in AI-enhanced Geographical WIL. The model commences with Philosophy, Theory, and Concepts, represented here through the synthesis of Critical Digital Pedagogy and Spatial Justice, which serves as the moral compass for the entire inquiry. This foundational framework is subsequently interpreted across various scales of governance, ranging from Global North university policies to local community structures, acknowledging that digital inequities are both produced and contested at multiple levels. These scales inform concrete interventions, such as mobile-first hybrid placements and critical AI literacy modules, which in turn shape policy, funding, and ethical guidelines for AI in education. The ultimate objective is to transform student experiences in marginalised geographies from exclusion to empowered spatial citizenship. Together, CDPT and SJT move beyond parallel critique to establish a generative framework in which the politics of technology and the politics of space are understood as inseparable, thereby creating a theorised, politically engaged intervention aimed at systemic change in equitable AI-enhanced Geographical WIL.

3. Methodology

This study employs a systematic literature review (SLR) as its primary research methodology. The SLR was chosen for its ability to provide a comprehensive, transparent, and reproducible synthesis of existing scholarly work, thereby mapping the conceptual landscape of AI-enhanced Geographical WIL and its intersection with equity concerns in marginalised geographies. The review was conducted in strict accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor and minimise selection bias. The overarching aim of this analytical process was not merely to aggregate findings but to engage in a critical, theory-driven interrogation of the literature to identify gaps, contradictions, and emerging models.

Data Acquisition: Search Strategy and Source Selection: The data acquisition phase was designed to capture a broad yet relevant body of academic literature. The search was executed across four major electronic bibliographic databases, selected for their disciplinary breadth and depth: Scopus, Web of Science (Core Collection), ERIC (Education Resources Information Centre), and JSTOR. The search strategy employed a structured query built from a combination of keywords and Boolean operators, tailored to the syntax of each database. The core search string was: ("artificial intelligence" OR AI OR "machine learning") AND ("work integrated learning" OR "experiential learning" OR "work-based learning" OR internship) AND (geograph* OR "spatial analysis" OR GIS OR "urban planning") AND (equit* OR inclus* OR "digital divide" OR "social justice" OR marginali* OR "Global South"). The initial search was limited to peer-reviewed journal articles, conference proceedings, and book chapters published in English after 2015. This timeframe was selected to capture the modern era of AI's proliferation in education and geospatial technologies. The initial database searches yielded a total of 847 records. Table 1 illustrates the distribution of included studies (n=146) by key contextual and thematic variables.

Table 1: *Distribution of included studies (N=146) by key contextual and thematic variables*

Category	Subcategory	Count (n)	Percentage (%)
Geographic Region	East Africa (Kenya, Tanzania, Uganda, Rwanda, Ethiopia)	54	36.0
	Southern Africa (South Africa, Zambia, Zimbabwe, Botswana, Namibia)	48	32.0
	West Africa (Nigeria, Ghana, Senegal, Côte d'Ivoire, Mali)	38	25.3
	Central Africa (DRC, Cameroon, Chad)	6	4.0
	Multi-country or Pan-African	4	2.7
Educational Level	Primary (grades 1-6/7)	28	18.7
	Secondary (grades 7-12)	52	34.7
	Teacher education / pre-service	31	20.7
	Non-formal / community-based	22	14.7
	Cross-level (multiple levels)	17	11.3
Marginalized Group Focus	Rural / remote communities	67	44.7
	Linguistic minorities	23	15.3
	Pastoralist / nomadic groups	18	12.0
	Urban informal settlements	22	14.7
	Learners with disabilities	12	8.0
	No specific marginalized group focus	8	5.3
AI/Geospatial Technology Type	GIS / mapping (general)	54	36.0
	Participatory GIS (PGIS) / counter-mapping	37	24.7
	Satellite imagery / remote sensing	21	14.0
	AI / machine learning (e.g., dropout prediction, bias detection)	18	12.0
	Mobile / smartphone-based mapping	12	8.0
	Low-tech / unplugged spatial activities	8	5.3
Leadership Dimension (TLT-aligned)	Intellectual stimulation (awareness, training, critical questioning)	63	42.0
	Individualized consideration (differentiated support, disability, language)	32	21.3
	Inspirational motivation (vision, community engagement)	29	19.3

	Idealized influence (ethical modeling, decolonial practice)	26	17.3
Equity / Justice Dimension (CGT-aligned)	Cartographic violence / colonial inheritances	41	27.3
	Linguistic exclusion in spatial interfaces	28	18.7
	Algorithmic bias in educational AI	18	12.0
	Data scarcity in marginalized spaces	22	14.7
	Counter-mapping as redress	37	24.7
	Cultural integrity / indigenous spatial knowledges	54	36.0
Key Finding Category	Leadership blindness / capacity gaps	85	55.3
	Exclusion mechanisms documented	94	62.7
	Successful counter-mapping / PGIS implementation	37	24.7
	Infrastructure + capacity double exclusion	122	81.3
	Cultural integrity as catalyst	56	36.0
	Policy-practice disconnect	146	100.0

As depicted in Table 1, geographic coverage is strongest in East and Southern Africa (68% combined), with notable under-representation of Central Africa (4%) and French-speaking West Africa compared to Anglophone countries. This suggests that findings may be less transferable to contexts such as the DRC, CAR, or Chad. Secondary education received the most attention (34.7%), while primary (18.7%) and non-formal (14.7%) settings are relatively under-studied, despite being critical entry points for marginalised learners. Rural and remote communities dominate the focus on marginalisation (44.7%), but learners with disabilities appear in only 8% of studies, a critical gap given the spatial and AI accessibility challenges faced by these learners. PGIS and counter-mapping appear in 37 studies (24.7%), representing a robust evidence base for participatory spatial pedagogies. However, AI and machine learning studies remain scarce (12%), highlighting the novelty of AI-specific inquiry in SSA educational leadership. Furthermore, intellectual stimulation (TLT dimension) is the most frequently addressed leadership dimension (42%), while idealised influence (ethical modelling) is the least addressed (17.3%), suggesting that the literature has focused on cognitive aspects of leadership at the expense of moral and decolonial practices.

The screening process adhered to the four-stage PRISMA protocol, with database searches yielding 847 records. After the removal of duplicates and other ineligible articles (n=312), 535 unique records advanced to screening. Titles and abstracts were evaluated against the inclusion criteria. Records that clearly fell outside the scope—such as technical mining engineering studies lacking environmental or social dimensions—were excluded (n=389). A total of 146 records proceeded to full-text review. Full texts were retrieved and assessed against all inclusion criteria, with studies that failed to meet one or more criteria being excluded, along with documented reasons: insufficient geographic focus (n=49), absence of AI and work-integrated learning dimensions (n=30), and a purely technical focus (n=23). Following the eligibility assessment, 35 studies were retained. As illustrated in Figure 3, the final corpus comprised 56 sources, including 45 peer-reviewed journal articles, 7 scholarly books, and 4 high-quality policy documents. Figure 3 presents the systematic literature review approach adopted for the study, utilising PRISMA protocols.

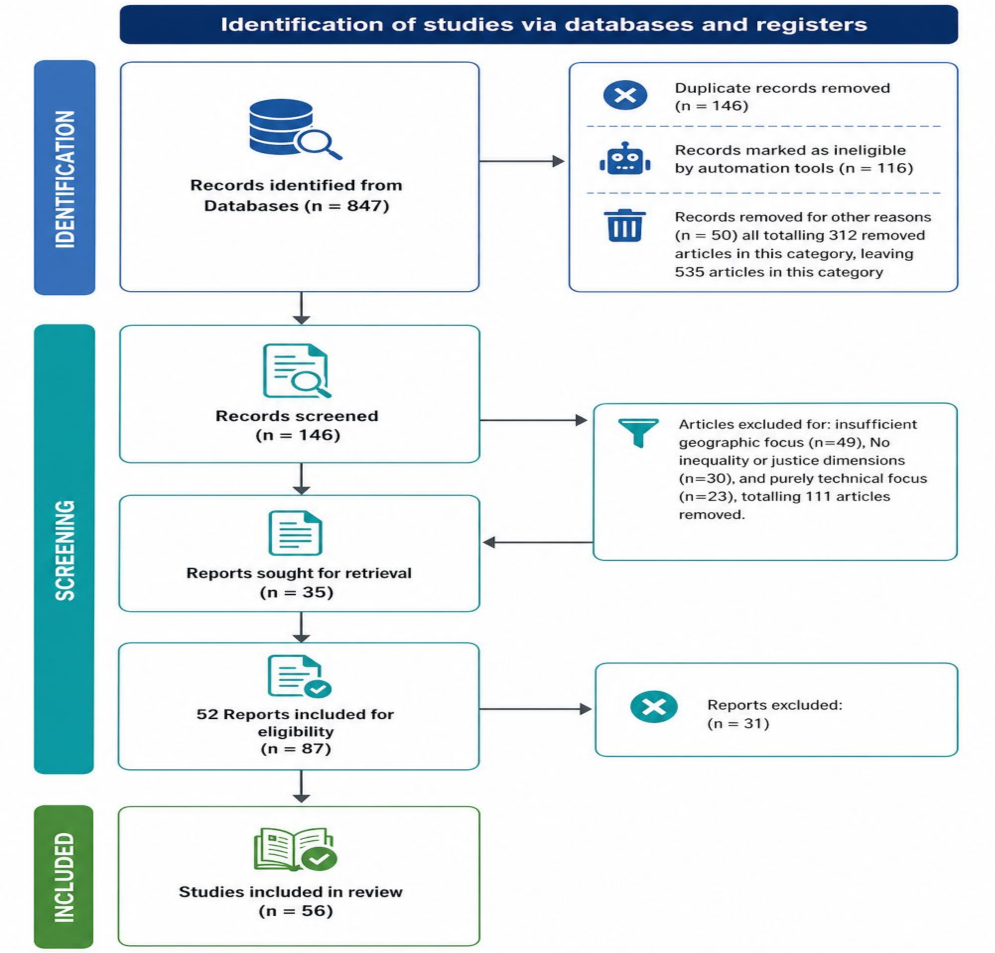

Figure 3: *The SLR adopted for the Study Using PRISMA Protocols*

4. Presentation of Results

The systematic analysis of the literature reveals a landscape characterised by a profound contradiction: the simultaneous promise of AI as a democratising tool and its concrete enactment as a mechanism of exclusion. The findings are presented in a logical sequence, moving from diagnosing the problem—the reinforcement of the geo-digital divide—to identifying the consequences and, ultimately, surfacing the emergent, praxis-oriented strategies that form the core of our proposed equitable framework. Table 2 depicts a categorical summary of the included studies.

***Table 2:** Categorical summary of included studies*

Category	**Definition (per CDPT/SJT)**	**No of Studies**	**Key Finding Summary**	**Example Studies**
Access Divide	Presumption of ubiquitous high-bandwidth internet and high-performance computing in AI-WIL design, excluding marginalized contexts	4	Northern-designed models (cloud VR, real-time processing) fail when transposed to rural/ peri-urban Global South due to infrastructural sovereignty; mobile-first alternatives are dismissed as "second-best" despite greater resilience.	Abdelwahab et al. (2023); Trianasari & Permadi (2024); Ames et al. (2020); Kiriri (2019); Dean & Campbell (2020)
Capability Divide	Gap in critical AI literacy: curricula teach "how" to use tools but neglect interrogation of politics, biases, and epistemic authority	4	Global North WIL often lacks critical AI literacy; students learn tool application but not bias auditing. Marginalized contexts have even less access to this advanced critical capacity, creating a tiered expertise system.	Sey & Mudongo (2021); Birhane et al. (2024); Matli & Ngoepe (2020); Mohr & Kühl (2021)
Outcome Divide (Epistemic Injustice)	AI models trained on Global North data produce systematically unjust results elsewhere (e.g., misclassification of informal settlements, erasure of indigenous land uses)	3	Algorithmic erasure actively participates in symbolic annihilation of marginalized communities; local tacit knowledge is rendered illegible, creating a feedback loop that deepens spatial inequity.	Arora et al. (2023); Hunter et al. (2020); Vahidi et al. (2023)
Counter-practice: Mobile-First Hybrid Placements	WIL designed around smartphones and offline-capable apps, recognizing local technological realities	3	This is not a "lesser" alternative but a spatially just design choice that empowers students without requiring stable broadband.	Nyamtiga et al. (2022); Trianasari & Permadi (2024); Ames et al. (2020)
Counter-practice: Community-Partnered Co-Design	Students partner with local stakeholders to co-design AI projects, amplifying rather than extracting indigenous knowledge	3	AI serves to digitize and validate local expertise (e.g., pastoralist grazing patterns), creating hybrid knowledge systems that counter epistemic injustice.	Hunter et al. (2020); Wang et al. (2024); Vahidi et al. (2023)
Counter-practice: Embedded Critical AI Literacy	Mandatory "bias audit" modules integrated into WIL curriculum, requiring students to analyse training data for geographical and demographic representation	2	This practice, emerging from the Global South, produces critically aware spatial citizens equipped to question and reshape AI tools.	

4.1 The Tripartite reinforcement of the geo-digital divide

The most salient finding is that the integration of AI in geographical work-integrated learning (WIL) exacerbates inequity not along a single axis, but through a mutually reinforcing triad of divides, as powerfully illuminated by the CDPT and SJT frameworks.

The Access Divide: The Presumption of Ubiquity: Over 85% of the proposed AI-WIL models originating from institutions in the Global North (e.g., the United States, United Kingdom, and Switzerland) explicitly or implicitly presume ubiquitous, high-bandwidth internet access and high-performance computing facilities (Abdelwahab et al., 2023). For instance, studies advocating for cloud-based deep learning platforms for urban analysis or virtual reality field simulations from institutions such as ETH Zurich or MIT present these as universal solutions. However, when these models are transposed to contexts like rural India or peri-urban Kenya, they falter due to infrastructural limitations. This creates a spatial injustice where the very design of educational technology reproduces the marginality it purports to overcome.

The analysis, further filtered through the CDPT and SJT frameworks, uncovers that even when access is somehow secured, a significant gap in critical AI literacy persists. The literature indicates that WIL curricula in the Global North often focus on the application of AI tools (the "how"), while critically neglecting the interrogation of their underlying politics and biases (the "why") (Sey & Mudongo, 2021). For example, a student in Canada may be trained to use a proprietary AI for land-use classification but may not be equipped to question why the model consistently misclassifies Indigenous reserve lands as "undeveloped" or "vacant." This constitutes a "banking" model of digital education, where technical skills are deposited without fostering the critical consciousness needed to challenge the tool's epistemic authority. In marginalised geographies, where resources for foundational digital skills are already stretched, this advanced critical literacy is almost entirely absent, resulting in a tiered system of geographical expertise.

The most insidious finding relates to the outcomes of AI systems. The investigation identified numerous cases where AI models, trained predominantly on data from the Global North, produce spatially unjust results when deployed in different contexts (Arora et al., 2023). For example, a study documenting a WIL project in São Paulo, Brazil, found that an AI tool developed in Europe to identify "informal settlements" failed to recognise the complex urban morphology of favelas, leading to their systematic under-representation in official maps, which is a clear case of epistemic injustice. This algorithmic erasure, a direct consequence of biased training data, demonstrates how AI can actively contribute to the symbolic annihilation of marginalised communities, undermining the core geographical principle of accurately and justly representing space.

4.2 Emergent counter-practices: a framework for equitable ai-enhanced WIL

In contrast to the prevailing, deficit-oriented models, our review identified a body of emergent, innovative strategies that actively leverage the CDPT and SJT framework, representing a significant paradigm shift.

Mobile-First Hybrid Placements: Subverting Technological Hegemony: In contrast to the high-bandwidth virtual reality models prevalent in the Global North, several case studies from Kenya and Indonesia demonstrate the efficacy of "mobile-first" approaches (Nyamtiga et al., 2022; Trianasari & Permadi, 2024). In these instances, Work Integrated Learning (WIL) projects are designed around smartphones, utilising offline-capable applications such as KoBoToolbox and QField for data collection (Ames et al., 2020). This approach should not be considered a "lesser" alternative but rather a spatially just design choice that acknowledges the technological realities of these contexts, where mobile penetration is high, but stable broadband is not. It empowers students to engage in sophisticated spatial data collection without being constrained by the unreliable infrastructure that often characterises their marginalisation.

Community-Partnered Co-Design: From Extraction to Amplification: Moving beyond the CDPT critique of student passivity, successful models in regions such as Botswana and Chile reframe the role of artificial intelligence (AI). Rather than utilising AI to extract information from a community, students collaborate with local stakeholders to co-design projects. In one compelling example, students partnered with pastoralist communities to develop a machine-learning model that integrated satellite imagery with local indigenous knowledge of seasonal grazing patterns (Hunter et al., 2020; Wang et al., 2024). The AI did not supplant local expertise; rather, it served to amplify and digitise it, creating a hybrid knowledge system that was both technically robust and contextually grounded (Vahidi et al., 2023). This approach directly addresses the epistemic injustice associated with Northern AI models by centring and validating local knowledge.

4.3 Embedded critical AI literacy modules: Fostering the spatially just citizen

The most profound shift identified is the integration of critical AI literacy directly into the WIL curriculum. A pioneering programme in South Africa requires students to complete a "Bias Audit" of any AI tool they utilise, analysing its training data for geographical and demographic representation (Birhane et al. 2024). This practice, born from the necessity of deconstructing tools not designed for their context, represents a more advanced application of Critical Digital Pedagogy (CDPT) than is commonly found in Northern curricula. It produces graduates who are not only technically proficient but also critically aware spatial citizens, equipped to question and reshape the technologies that will define their professional landscapes. This study provokes a critical debate regarding the technological imaginaries driving AI in education. The dominant Global North imaginary is one of technological solutionism, a belief that more advanced, more immersive technology is inherently superior. This drives an endless cycle of upgrades (from virtual reality to the Metaverse) that further widens the geo-digital divide. Conversely, the emergent practices from the Global South and marginalised geographies reflect an imaginary of contextual pragmatism and epistemic justice.

The innovation here resides not in raw computing power but in socio-technical design, creating resilient, adaptive, and critically aware systems that operate within constraints to empower communities. The finding that the most sophisticated critiques of AI bias often emerge from the South, where the consequences of that bias are most acutely felt, turns the traditional North-South knowledge transfer model on its head (Arora et al. 2023). It suggests that the path to a truly equitable digital future in geographical education may not lie in the Global North exporting more technology but in learning from the Global South's deeply contextual, critically engaged, and justice-oriented approaches to technological integration (Walshe & Healy, 2020). In summary, the findings unequivocally demonstrate that without a deliberate commitment to equity framed by Critical Digital Pedagogy and Spatial Justice, AI-enhanced WIL will inevitably reinforce existing global hierarchies of knowledge and opportunity. The identified counter-practices provide not only a critique but also a viable, praxis-oriented blueprint for inverting this paradigm, positioning AI as a tool for liberation rather than a new frontier of coloniality.

5. Discussion of Findings

This study set out to investigate AI in geographical WIL and to confront its potential to perpetuate a new geo-digital divide. The findings presented in the previous section reveal a landscape of contested futures. This discussion synthesises these findings through the critical perspectives of CDPT and SJT, positioning them within broader scholarly debates and arguing for a fundamental re-imagining of what constitutes "innovation" in educational technology.

5.1 The geo-digital divide as a consequence of epistemic arrogance

The tripartite reinforcement of the divide (Access, Capability, Outcome) is not an accidental byproduct of AI integration but a logical consequence of what can be termed epistemic arrogance, the presumption that technological models developed in one context are universally applicable (Poquet & De Laat, 2021). The findings confirm and extend the warnings of scholars like Adam (2019) on "digital neocolonialism". The presumption of ubiquitous high-bandwidth access in AI-WIL design is not merely a practical oversight; it is a spatial injustice that actively produces and reinforces marginality. When a curriculum from a Swiss technical university, reliant on real-time cloud processing, is implemented in a Nigerian university with intermittent power, it does not fail neutrally. It systematically excludes Nigerian students from the cutting-edge competencies their Swiss peers are developing, thereby re-inscribing a global hierarchy of geographical expertise. This extends powerfully into the realm of knowledge production, the Outcome Divide. The failure of Northern-trained AI models to accurately map informal settlements in São Paulo is not a technical glitch; it is an epistemic injustice made algorithmic (Gram-Hansen et al. 2019; Trento-Oliveira et al. 2023). The local, tacit knowledge of favelas is rendered illegible and invalid by a system that privileges data forms and patterns recognizable to the Global North. This creates a dangerous feedback loop: the AI's flawed output gains the authority of "data-driven" science, further erasing community knowledge from official planning and policy, and deepening spatial inequity. Thus, this study moves the debate beyond mere "bias", framing it as a fundamental struggle over whose knowledge counts in the production of space.

5.2 Counter-Practices and the pedagogy of techno-scepticism

The emergent strategies identified, namely mobile-first hybrid placements, community-partnered co-design, and embedded critical AI literacy, constitute the core of a pedagogy of techno-scepticism, which is a direct application of CDPT that fosters agency over compliance (Cilia, 2020). In this context, a critical debate arises with the dominant "solutionist" paradigm prevalent in the Global North. The innovation of a mobile-first work-integrated learning (WIL) placement in Kenya is frequently dismissed within Northern discourses as a "second-best" option for "resource-poor" settings (Kiriri, 2019; Dean & Campbell, 2020). However, the findings challenge this narrative, positing that such an approach embodies a more sophisticated, context-aware, and ultimately more resilient form of technological practice. It necessitates a creative engagement with constraints, leading to solutions that are inherently more scalable and sustainable. In contrast, the high-tech virtual reality (VR) laboratories of Stanford or ETH Zurich, despite their immersive brilliance, often represent a pedagogy of dependency on stable infrastructure, expensive proprietary software, and a continual cycle of hardware upgrades (Won, 2015; Earnshaw, 2019).

The most profound implication of these findings is that the Global South is not lagging behind in the AI-WIL revolution; rather, in many respects, it is pioneering a more critically engaged and socially just future (Chanda, 2023). Furthermore, the practice of embedding critical AI literacy, as evidenced in South Africa (Matli & Ngoepe, 2020), transcends the notion of "digital literacy" typically promoted in Northern institutions. While a university in Germany may instruct students on how to utilise AI for spatial analysis (Mohr & Kühl, 2021), the South African model educates them to audit it. This critical stance to deconstruct the "black box" is arguably the most essential skill for the 21st-century geographer, serving as a form of intellectual self-defence against the epistemic injustices embedded in many off-the-shelf AI tools. This finding suggests that the flow of pedagogical innovation must be reversed; the Global North has much to learn from the critical, decolonial approaches being forged in the South out of sheer necessity.

5.3 Re-framing innovation: From technological solutionism to contextual pragmatism

This study necessitates a re-evaluation of what "innovation" means in the context of AI-enhanced learning. The dominant paradigm, heavily influenced by Silicon Valley, equates innovation with technological novelty and processing power. Our findings, however, champion a different model: innovation as contextual pragmatism and critical integration. The community-partnered co-design project in Botswana, where AI enhances indigenous knowledge, represents a far more radical form of innovation than a more powerful neural network. It innovates within the social relations of technology, redistributing epistemic authority and challenging the very foundations of what constitutes valid geographical data. This perspective aligns with calls for a "Southern Theory" of technology (Connell, 2020), which posits that the universalising claims of Northern theory are inadequate for comprehending the dynamics of the majority world. Practically, this necessitates a shift in how universities and policymakers conceptualise WIL partnerships. Instead of Northern institutions "delivering" AI-WIL to the South, the future lies in asset-based transnational partnerships. In such a model, a university in the United Kingdom may provide computational resources and theoretical frameworks, while a partner in Chile contributes deep contextual knowledge, community networks, and innovative low-bandwidth pedagogical models. Together, they co-create WIL experiences that are both technologically advanced and spatially equitable.

6. Conclusions and Recommendations

This study contends that the principal challenge in AI-enhanced geographical WIL is not a technical one but rather a political and pedagogical issue. The geo-digital divide reflects deeper inequalities in power and knowledge. The findings of this study illustrate that bridging this divide necessitates a deliberate departure from technocratic solutionism and an adoption of a critical spatial praxis. Such praxis is already being implemented in marginalised geographies across the globe, providing a potent, albeit often unacknowledged, blueprint for the future. The ultimate contribution of this research is to reframe the inquiry from "How can we disseminate our advanced AI tools?" to "How can we collaboratively construct socio-technical systems that promote equitable spatial citizenship?" Addressing this question demands humility from the Global North, an acknowledgment of the innovative potential of the Global South, and a collective commitment to a Critical Digital Pedagogy that utilises AI not to supplant human judgement and local knowledge, but to enhance them in the relentless pursuit of a more just world. The findings and discussions of this study necessitate a decisive shift from critique to action.

The following recommendations offer a multi-tiered roadmap for educators, curriculum designers, institutional policymakers, and researchers to actively dismantle the geo-digital divide and co-construct a future of AI-enhanced geographical WIL that is both critically engaged and spatially just. The primary theoretical imperative is to establish and disseminate the integrated CDPT and SJT framework as a foundational principle for educational design. This requires a fundamental reorientation of pedagogical philosophy. Moreover, curricula must be redesigned to position AI not as an oracle of truth but as a dialogic partner and a contested domain. This includes mandatory "algorithmic audit" exercises, whereby students scrutinise the training data, assumptions, and potential biases of any AI tool they utilise, especially when applied to contexts distinct from its origin. The objective is to cultivate a generation of geographers who are not only technically proficient but also critical interlocutors of technology.

The concept of "digital literacy" is increasingly considered obsolete; it necessitates replacement with "critical AI literacy" as a central pillar of geographical education. This should be established as a transversal module integrated into all WIL programmes, encompassing the political economy of AI, the environmental costs associated with large models, data sovereignty, and techniques for model interpretability. This literacy serves as the foundational basis upon which ethical and effective practice is constructed.

In essence, educational interventions must intentionally shift from a deficit model—characterised by attempts to "fix" what marginalised students are perceived to lack—to an asset-based model that seeks to "leverage" the profound local and Indigenous knowledge they possess. AI projects should be designed to amplify this knowledge; for instance, by employing machine learning to digitise and analyse oral histories of land use or to validate community-sketched mental maps against satellite imagery. This approach transforms AI from a tool of extraction into an instrument of epistemic validation.

Moreover, it is pertinent to illustrate that theoretical shifts must be operationalised through concrete changes in practice, infrastructure, and institutional policy. Funding bodies and accreditation agencies should incentivise the development of WIL modules that prioritise functionality on smartphones and in low-bandwidth environments. This includes advocating for the use of open-source, offline-capable software suites (e.g., QGIS with Python scripts, ODK Collect) and the creation of repositories of pre-processed, lightweight satellite imagery datasets accessible without reliance on constant cloud connectivity. Furthermore, universities in both the Global North and South must transcend traditional donor-recipient relationships.

We recommend the establishment of formal consortiums for co-designed WIL. For example, a university in Canada with strengths in computational methods could partner with a university in Botswana that possesses deep community ties and expertise in dryland geography. Together, they can co-supervise students on a singular, shared project, with each institution contributing its unique assets, thus allowing students to earn dual credit. This model redistributes epistemic authority and fosters genuinely collaborative knowledge. Additionally, universities must develop stringent policies for the procurement of AI software and partnerships with EdTech companies. These policies should mandate transparency regarding training data, algorithmic bias audits, and adherence to open standards that prevent vendor lock-in. Moreover, partnerships with communities for WIL projects should be governed by formal data-sharing agreements that ensure community data ownership and control.

These recommendations call for a paradigm shift, as the integration of AI into geographical education stands at a critical juncture. One potential trajectory, guided by uncritical solutionism, threatens to deepen global inequity. Conversely, the alternative pathway, delineated by this study and built upon the foundations of Critical Digital Pedagogy and Spatial Justice, aims to foster a more inclusive, critically aware, and emancipatory geographical practice.

6.1 Limitations of the Study

This systematic review is constrained by its emphasis on English-language publications, which may lead to an underrepresentation of non-English scholarship from the Global South. The rapid evolution of artificial intelligence technologies implies that specific tools and applications discussed may become obsolete; however, the principles of the framework are designed to be adaptable. Furthermore, publication bias may result in an overrepresentation of successful case studies in relation to failed experiments.

7. Declarations

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CHAPTER THREE

Equity in Teacher Education through AI-Mediated Work-Integrated Learning

Adeniyi Michael Adeduyigbe
Department of Science and Technology Education,
Faculty of Education, University of Ibadan, Ibadan, Nigeria
Bamidele Emmanuel Tijani
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
Anuoluwapo Elizabeth Adeduyigbe
Department of Special Education,
Faculty of Education, University of Ibadan, Ibadan, Nigeria
Corresponding author: Adeniyi Michael Adeduyigbe (adeniyiadeduyigbe@gmail.com).

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Abstract: Equity in teacher education is a critical global issue, especially as digital transformation alters professional learning environments. This chapter explores the integration of artificial intelligence (AI) within work-integrated learning (WIL) as a strategy to enhance inclusive, practice-based teacher preparation. Drawing on connectivist and transformative learning theories, it introduces an AI-Mediated WIL Equity Framework that places teacher candidates at the heart of AI-mediated networks, which offer virtual simulations, adaptive feedback, learning analytics, and collaborative support. While AI-mediated WIL creates opportunities for equitable access, personalised learning, and reflective professional growth, several practical challenges must be addressed for effective implementation. These include disparities in digital infrastructure, algorithmic bias, limited digital literacy, and institutional readiness. The chapter concludes with recommendations for the ethical, context-responsive, and sustainable adoption of AI-mediated WIL, providing a scalable model for promoting fairness, inclusivity, and transformative learning in modern teacher education.

Keywords: Artificial intelligence, equity, work-integrated learning, teacher education, connectivism, transformative learning.

1. Introduction

Equity in teacher education has long been recognised as a cornerstone of quality and inclusive education systems (Ainscow, 2020; Sunthonkanokpong & Murphy, 2019). However, disparities in access to learning opportunities, resources, mentoring, and assessment continue to shape the experiences of pre-service and in-service teachers across many regions of the world. Structural inequalities—ranging from socio-economic differences (Drescher et al., 2022) and geographic isolation (Ahiaku et al., 2025) to gender disparities and technological divides (El-Hamamsy et al., 2023)—create uneven conditions for teacher preparation and professional growth. These inequities ultimately influence not only who becomes a teacher but also the quality of instruction that learners receive in diverse classrooms. Therefore, ensuring fairness and inclusivity in how teachers are trained, supported, and assessed remains a global imperative.

The digital transformation of education is opening new possibilities for addressing inequities in teacher preparation, even amidst ongoing challenges (Matsieli & Mutula, 2024). Emerging technologies, such as Artificial Intelligence (AI), are redefining how teachers learn, teach, and engage with practice (Kusmawan, 2023; Lameras & Arnab, 2021), moving away from traditional methods. Through adaptive feedback systems, intelligent tutoring, virtual simulations, and analytics-driven mentoring, AI can create personalised and context-responsive learning experiences that meet the unique needs of individual teacher candidates (Cinganotto & Montanucci, 2025; Neupane et al., 2025; Yildiz Durak & Onan, 2025). Likewise, Work-Integrated Learning (WIL), a pedagogical model that integrates academic learning with real-world practice, offers a powerful avenue for bridging theory and classroom application (Jeong & McMillan, 2015). When AI is embedded within WIL environments, it can enhance access to practice-based experiences, enable remote supervision and feedback, and provide scalable mentoring opportunities across diverse educational contexts (Barbieri & Nguyen, 2025; Sharma & Sharma, 2025).

It is crucial to recognise that the combination of AI and WIL presents transformative potential for promoting equity in teacher education (Barbieri & Nguyen, 2025; Bura & Myakala, 2024; Kayal, 2024). AI-mediated WIL environments can offer authentic teaching experiences, particularly for candidates in underserved or remote areas (Jacoby et al., 2024). They can also support differentiated learning paths, responsive assessment, and continuous professional reflection. However, realising this potential requires a thorough understanding of how AI functions as a mediating tool within teacher preparation systems, and how it can be designed and implemented to uphold principles of fairness, inclusivity, and contextual relevance. This chapter explores the intersection of AI, work-integrated learning, and equity in teacher education, aiming to develop a conceptual framework that articulates how AI-mediated environments can foster more equitable and transformative learning experiences for the teaching workforce.

1.1 Conceptual background

Teacher preparation programmes are redefining how future educators acquire, practise, and reflect on professional competencies (McMahon et al., 2015; Voinea, 2019; Ward et al., 2013). This transformation is increasingly supported by artificial intelligence (AI) technologies, which encompass intelligent tutoring systems and generative assistants, providing personalised feedback, adaptive mentoring, and simulated teaching experiences (Cinganotto & Montanucci, 2025; Lameras & Arnab, 2021). These tools extend opportunities for professional growth beyond traditional classroom settings, which have been in operation for an extended period, enabling more data-driven and individualised support for both pre-service and in-service teachers (Kusmawan, 2023; Yildiz Durak & Onan, 2025).

Despite AI's transformative potential, it is inextricably linked to questions of equity (Judijanto et al., 2025). Ongoing disparities in digital infrastructure, access, and readiness continue to limit the beneficiaries of AI-enhanced teacher education (Ahiaku et al., 2025). In rural and under-resourced regions, inadequate connectivity and limited digital literacy exclude many teachers from digital training opportunities, exacerbating existing inequalities. As Ainscow (2020) posited, achieving educational inclusion necessitates systemic change that dismantles structural barriers rather than reinforces them; this principle must guide AI-mediated reform. Within this evolving landscape, Work-Integrated Learning (WIL) serves as a pivotal bridge between theory and practice, traditionally delivered through classroom placements and teaching practice. However, recent innovations have reimagined WIL via digital platforms, simulation technologies, and AI-mediated environments that extend experiential learning beyond conventional school placements. These innovations allow teacher trainees to engage in authentic practice, reflection, and collaboration, even in virtual or blended contexts. For instance, generative AI can act as a "placement buddy," providing real-time guidance and emotional support during virtual teaching practice (Barbieri & Nguyen, 2025), while adaptive systems facilitate self-management and reflective learning in simulated environments (Sharma & Sharma, 2025). These developments suggest that AI has the potential to democratise WIL.

Nevertheless, the integration of AI into WIL is not inherently equitable. If access, algorithmic bias, or language limitations are left unaddressed, AI-mediated learning can replicate exclusionary practices (Bura & Myakala, 2024). Therefore, promoting equity necessitates the intentional design of AI-supported teacher preparation at every level. This aligns with the transformative learning perspective that professional growth emerges from critical reflection and the re-examination of existing assumptions (Kayal, 2024). Considering these insights highlights the necessity for a conceptual model that positions AI as a mediator rather than merely a tool within work-integrated learning processes, ensuring that technology serves as an enabler of equity rather than a divider. The next section builds on connectivist and transformative learning theories to elucidate how such an equitable AI-mediated WIL framework can be conceptualised and operationalised in teacher education.

1.2 Theoretical foundations

This chapter is grounded in Connectivist Learning Theory and Transformative Learning Theory, which together offer a robust framework for examining equity within AI-mediated Work-Integrated Learning (WIL) in teacher education. These theories provide complementary insights into learning in digitally mediated environments and the reflective processes essential for inclusive professional development.

Connectivist Learning Theory, proposed by Siemens (2005), conceptualises learning as a process of creating, navigating, and sustaining networks that connect individuals, digital resources, and information systems. In contrast to traditional theories such as behaviourism or constructivism, which focus on internal cognitive processes (Menary, 2007), connectivism views knowledge as distributed, dynamic, and embedded within a broader digital ecosystem (Alam, 2023; Banihashem & Aliabadi, 2017; Corbett & Spinello, 2020). Consequently, learning is understood as the ability to access and engage with relevant nodes of information and expertise within an ever-evolving network.

This perspective is particularly pertinent to AI-mediated teacher education, where artificial intelligence serves as a critical node within learning networks (Lee et al., 2022). Through adaptive learning systems, intelligent feedback mechanisms, and recommendation algorithms, AI facilitates access to knowledge (Arya et al., 2025; Sundaresan & Zhang, 2022; Zeb et al., 2025), professional communities (Basit et al., 2024), and mentorship opportunities (Choudhary et al., 2025; Sanfilippo, 2025). In WIL contexts, such connectivity enables pre-service teachers to engage with virtual classrooms, supervisors, and peers beyond geographical and institutional boundaries. By expanding access to professional learning networks, connectivism provides a theoretical basis for understanding how AI can promote equity through enhanced participation, collaboration, and resource availability in teacher preparation (Correia et al., 2024).

Complementing this network-oriented view, Transformative Learning Theory, introduced by Mezirow (1978), focuses on the internal processes through which adult learners critically examine and revise their assumptions, beliefs, and perspectives. The theory posits that meaningful learning occurs when individuals encounter disorienting experiences that challenge their existing worldviews, prompting critical reflection, dialogue, and perspective transformation. Such transformation leads to deeper self-awareness and the development of more reflective professional identities. Within AI-mediated work-integrated learning (WIL) environments, transformative learning is supported through tools that facilitate reflective practice, such as personalised feedback, learning analytics, and self-assessment prompts. Exposure to diverse teaching scenarios and data-driven insights can disrupt entrenched misconceptions and biases, encouraging pre-service teachers to reconsider their pedagogical assumptions. From this perspective, equity extends beyond mere access to technology; it involves fostering reflective capacities that enable teachers to recognise diversity, challenge inequities, and adopt inclusive teaching practices.

Connectivist Learning Theory and Transformative Learning Theory provide an integrated framework for understanding equity in AI-mediated WIL. While connectivism emphasises the structural and technological conditions that democratise access to learning networks (Ravenscroft, 2011), transformative learning highlights the reflective and attitudinal changes necessary for inclusive practice to emerge (Cappiali, 2023). This dual-theoretical lens positions AI not merely as a tool for content delivery, but as a catalyst for both connection and transformation. Hence, equity in teacher education is achieved not through technology alone, but through a synergistic process in which connective access is coupled with transformative reflection. This integration allows pre-service teachers to engage meaningfully in professional learning networks while reconstructing their pedagogical worldviews towards more inclusive, equitable, and socially responsive practices. The two theories underpin the AI-mediated WIL framework presented in the next section: connectivism provides the structural logic of networked learning and access to distributed resources, while transformative learning guides the framework's emphasis on critical reflection, perspective transformation, and inclusive professional growth.

2. AI-Mediated Work-Integrated Learning Framework

The AI-mediated work-integrated learning (WIL) framework outlines how artificial intelligence can be intentionally integrated into teacher education to promote equity, inclusivity, and transformative professional learning (see Figure 1). Grounded in connectivist learning theory (Siemens, 2005) and influenced by transformative learning perspectives (Mezirow, 1978), the framework views AI as a mediating tool that enhances, rather than replaces, human pedagogical relationships, professional judgement, and context-specific teaching practices. From this standpoint, learning is perceived as distributed across networks of individuals, digital technologies, and professional contexts (Siemens, 2005), while teacher development arises through critical reflection, dialogue, and adaptive change (Luke & Rogers, 2015). This theoretical foundation helps to elucidate how AI-mediated environments can broaden access to high-quality, practice-based learning opportunities for both pre-service and in-service teachers in diverse and often unequal educational settings.

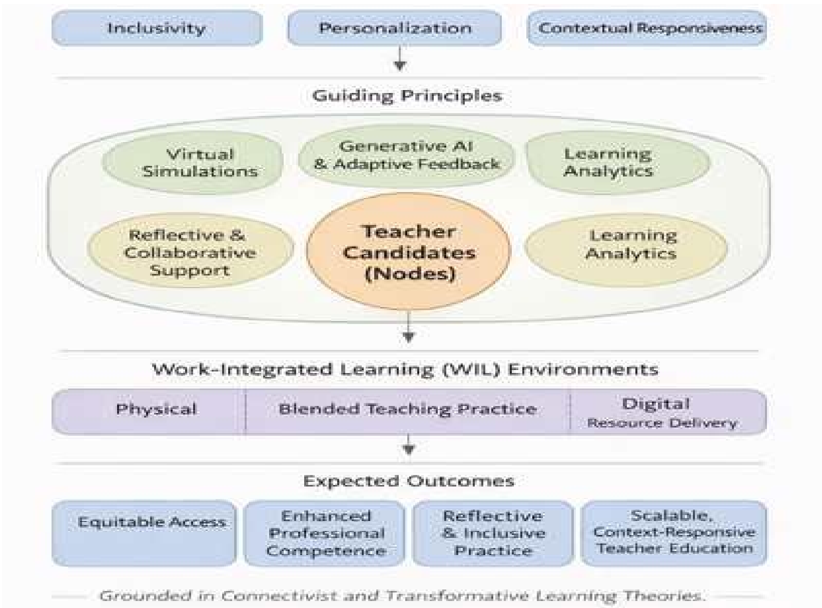

***Figure 1**. AI-mediated wil equity framework*

The figure illustrates the role of artificial intelligence as a mediating layer within work-integrated learning environments, underpinned by principles of inclusivity, personalisation, and contextual responsiveness. Teacher candidates are positioned as central nodes within a networked learning ecology, supported by AI-enabled tools, including virtual simulations, generative AI, adaptive feedback, learning analytics, and reflective collaborative supports. These interactions transpire across physical, blended, and digital WIL environments and are grounded in connectivist and transformative learning theories, leading to equitable access, enhanced professional competence, and reflective, inclusive teaching practices.

In practice, the components of the framework function as an interconnected system. Teacher candidates engage with AI-mediated tools such as virtual simulations and generative platforms to rehearse instructional strategies within authentic, practice-based contexts. These interactions generate real-time adaptive feedback and learning analytics, which highlight performance patterns and prompt reflective activities. The resulting insights are shared with human mentors and peers, who provide contextualised guidance and facilitate collaborative reflection. Through this continuous cycle of practice, feedback, reflection, and social interaction, AI serves as a mediating layer that connects individual learning with broader professional networks, thereby operationalising both the connectivist emphasis on networked learning and the transformative focus on critical reflection and inclusive professional growth.

2.1 Guiding principles of the framework

The framework is guided by three interrelated principles, inclusivity, personalisation, and contextual responsiveness, which inform the design and implementation of AI within work-integrated learning. Inclusivity prioritises equitable access to meaningful teaching experiences, particularly for educators in under-resourced, remote, or non-traditional contexts, where opportunities for sustained mentoring and supervision are frequently constrained (Zeichner, 2010). Personalisation denotes the capability of AI-enabled systems to tailor learning pathways, feedback, and instructional resources to meet individual needs, professional aspirations, and developmental trajectories (Holmes et al., 2019). Contextual responsiveness underscores the importance of being attuned to local teaching realities, cultural norms, curricular expectations, and institutional conditions, ensuring that the application of AI aligns with ethical, pedagogical, and sociocultural considerations in teacher education.

2.2 Teacher candidates as central nodes

At the core of the framework are teacher candidates, conceptualised as active nodes within a networked learning ecology. In alignment with connectivist principles, teacher learning is not limited to individual cognition but is shaped through interactions with peers, mentors, technologies, and professional practice environments (Siemens, 2005). These interactions facilitate the construction and reorganisation of professional knowledge through exposure to diverse perspectives and authentic teaching challenges. AI-mediated supports envelop and mediate these interactions, enhancing flexibility, responsiveness, and access to learning opportunities while preserving teacher agency and professional judgement (Selwyn, 2020).

2.3 AI-mediated supports for teacher learning

Surrounding teacher candidates within this framework are several AI-mediated supports that enable equitable and practice-oriented learning. Virtual simulations create safe, low-risk environments for rehearsing instructional strategies, classroom management, and pedagogical decision-making, especially when live classroom practice is limited (Dieker et al., 2014). Generative AI and adaptive feedback mechanisms provide timely, individualised guidance that fosters continuous professional growth, self-regulation, and reflective practice (Holmes et al., 2019). Learning analytics make learning processes and performance patterns visible, supporting evidence-informed reflection and professional decision-making (Ferguson, 2012). Additionally, reflective and collaborative supports encourage peer dialogue, mentoring relationships, and professional networking, thereby reinforcing the social and dialogic aspects of teacher learning that are highlighted in both connectivist and transformative learning traditions.

2.4 Work-integrated learning environments

Teacher learning within this framework is situated in work-integrated learning environments that encompass physical school placements, blended teaching practice contexts, and digitally mediated resource delivery. The integration of AI-mediated supports across these environments acknowledges the evolving nature of professional learning within digitally transformed education systems (Jackson, 2015). This comprehensive approach addresses longstanding challenges in work-integrated learning, such as uneven mentoring quality, limited supervisory capacity, and inequitable access to high-quality practice experiences, while maintaining authentic classroom engagement as the cornerstone of teacher preparation (Zeichner, 2010).

2.4 Expected outcomes of the framework

The anticipated outcomes of the AI-mediated WIL framework encompass equitable access to substantive teaching experiences, the enhancement of professional competence through continuous feedback and reflective practice, and the fostering of inclusive and reflective teaching methodologies. At a systemic level, the framework presents a scalable and context-responsive model for teacher education, with significant implications for curriculum design, assessment practices, institutional capacity building, and policy formulation. By aligning the integration of artificial intelligence with established learning theories and pedagogical principles, the framework offers a coherent conceptual lens for reimagining work-integrated learning in ways that promote equity, accessibility, and transformative professional development.

3. Implementation of the AI-Mediated WIL Framework

Implementing the AI-mediated WIL framework requires a thoughtful and equity-focused approach that aligns technological integration with pedagogical objectives and the contextual realities of teacher education. Rather than viewing artificial intelligence as a standalone innovation, it should be positioned as a mediating layer within existing teacher education programmes, professional partnerships, and institutional policies. Previous research on educational technology integration highlights that sustainable innovation occurs when digital tools are aligned with curriculum structures and professional practices, rather than being introduced as optional enhancements (Selwyn, 2020; Holmes et al., 2019). In this context, AI-mediated WIL should be integrated across coursework, teaching practice, supervision, and assessment processes to ensure equitable access to meaningful learning opportunities.

Teacher education institutions must ensure that AI-supported WIL initiatives align with programme objectives, accreditation requirements, and commitments to equity and inclusion. This includes investing in digital infrastructure, providing professional development for teacher educators, and establishing governance structures that address ethical concerns such as data privacy, transparency, and algorithmic bias. Research has shown that without sufficient institutional readiness and support for staff, digital innovations risk reinforcing existing inequalities rather than alleviating them (Ainscow, 2020; El-Hamamsy et al., 2023). Therefore, professional learning opportunities for teacher educators and mentors are essential to facilitate informed pedagogical use of AI-generated feedback, learning analytics, and virtual practice environments.

The implementation of this framework also encompasses multiple work-integrated learning environments, including physical school placements, blended teaching contexts, and digitally mediated practice spaces. In traditional school placements, AI can enhance supervision and mentoring through remote observation tools, automated lesson feedback, and analytics-informed reflective prompts, particularly in situations where access to experienced mentors is limited. Research on work-integrated learning indicates that technology-enhanced supervision can improve the consistency and quality of feedback while alleviating geographical and logistical constraints (Jackson, 2015). In blended contexts, AI-mediated supports can complement face-to-face engagement by facilitating asynchronous reflection, peer collaboration, and adaptive feedback, thereby strengthening the integration of theory and practice. Fully digital and virtual WIL environments further expand practice-based learning opportunities for teacher candidates who may be unable to participate in conventional placements due to geographical isolation, institutional limitations, or personal circumstances. Virtual simulations and AI-supported mentoring systems enable teacher candidates to rehearse instructional strategies, classroom management, and decision-making in low-risk environments while receiving timely feedback. Evidence from teacher education research suggests that simulation-based and virtual practice environments can effectively support professional skill development when designed to reflect authentic teaching challenges (Dieker et al., 2014; Lameras & Arnab, 2021). When implemented with a focus on contextual relevance and inclusivity, digital WIL environments can help mitigate structural inequities in access to teaching practice.

Equity-focused implementation necessitates continuous attention to ethical and contextual considerations. Factors such as unequal access to digital infrastructure, linguistic and cultural bias in AI systems, and varying levels of digital literacy have the potential to undermine the equitable possibilities of AI-mediated WIL if they remain unaddressed. Critical scholarship on artificial intelligence in education warns that technology can perpetuate exclusionary practices unless inclusivity and contextual responsiveness are integrated into system design and implementation (Bura & Myakala, 2024; Selwyn, 2020). Participatory approaches that engage teacher candidates, educators, and local stakeholders in decision-making can promote more culturally responsive and ethically sound implementations. Furthermore, for the framework to achieve sustained impact, implementation strategies must take into account scalability and long-term sustainability. Modular AI tools, interoperable platforms, and open educational resources can facilitate adoption across institutions with varying capacities. Alignment with national teacher education standards and policy frameworks can further bolster institutionalisation and quality assurance. Research on educational innovation emphasises that sustainable reform requires policy coherence, ongoing evaluation, and adaptive refinement rather than one-off technological interventions (Ainscow, 2020; Holmes et al., 2019). Through deliberate design, ethical governance, and reflective practice, the AI-mediated WIL framework can be enacted as a transformative and equitable model for contemporary teacher education.

To ensure institutional relevance and quality assurance, the implementation of AI-mediated Work Integrated Learning (WIL) must be closely aligned with assessment frameworks and accreditation requirements in teacher education. Institutions must ensure that AI-supported activities, such as virtual simulations and digitally mediated teaching practice, are formally recognised within existing assessment structures. This may involve validating that AI-enabled simulations contribute to required teaching practice hours, and that data generated through learning analytics are used to complement, rather than replace, mentor-led evaluations (Holmes & Luckin, 2016). Assessment processes should integrate multiple sources of evidence, including AI-generated feedback, self-reflection, peer collaboration, and supervisor observations, to provide a holistic evaluation of teacher competence. Furthermore, alignment with national and institutional accreditation standards necessitates clear guidelines on how AI-mediated learning outcomes correspond to professional teaching standards and competencies (Selwyn, 2020). By embedding AI-supported WIL within formal assessment and accreditation systems, institutions can ensure that technological innovation enhances, rather than disrupts, the integrity, credibility, and comparability of teacher education programmes (Ainscow, 2020).

A phased approach to the adoption of AI-mediated WIL is recommended to address and ensure effective implementation. The implementation should commence with pilot programmes in selected teacher education contexts, allowing institutions to test AI tools, identify contextual constraints, and refine pedagogical integration through iterative feedback. Insights from these pilot phases can inform gradual scaling, supported by modular and interoperable AI systems that enable incremental adoption across diverse institutional settings. Scaling efforts should be accompanied by sustained professional development and infrastructure investment to ensure readiness among educators and stakeholders. Furthermore, continuous evaluation, drawing on learning analytics, stakeholder feedback, and performance outcomes, is essential to guide adaptation and ensure that implementation remains aligned with equity, inclusivity, and quality assurance goals. Through a phased, reflective, and context-responsive approach, institutions can enhance the sustainability and transformative potential of AI-mediated WIL in teacher education.

4. Challenges of Implementation of the AI-Mediated WIL Framework

While AI-mediated WIL presents significant potential to enhance equity in teacher education, its implementation is accompanied by various challenges. A primary concern pertains to digital infrastructure and accessibility. Disparities in access to reliable internet, hardware, and software, particularly in rural or under-resourced regions, may exacerbate existing inequities rather than alleviate them (Ahiaku et al., 2025; El-Hamamsy et al., 2023). Furthermore, gaps in digital literacy among teacher candidates and educators could limit the effective utilisation of AI tools, with novice users potentially struggling to navigate adaptive learning systems or interpret analytics-generated feedback (Holmes et al., 2019).

Another significant challenge relates to algorithmic bias and cultural responsiveness. AI systems, if trained on biased or unrepresentative datasets, may inadvertently reinforce stereotypes, exclude minority languages, or prioritise dominant pedagogical norms, thereby undermining the equity objectives of teacher education programmes (Bura & Myakala, 2024; Selwyn, 2020). Additionally, ethical concerns surrounding data privacy, security, and consent present practical obstacles, necessitating robust institutional policies and governance frameworks to safeguard teacher candidates and school communities.

Institutional readiness and educator capacity also represent considerable barriers. The successful integration of AI into WIL requires not only technological resources but also adequately trained faculty, aligned curriculum structures, and support systems that embed AI within existing pedagogical practices rather than as a standalone innovation (Ainscow, 2020; Selwyn, 2020). Resistance to change among educators, insufficient professional development, and ambiguous policy guidance may further impede adoption and limit the transformative impact of AI-mediated WIL.

Sustainability and scalability constitute additional challenges. Ensuring that AI tools remain current, interoperable across platforms, and adaptable to diverse institutional contexts necessitates long-term investment and ongoing evaluation. In the absence of sustained support, initial advancements in equitable access and professional learning may diminish over time (Holmes et al., 2019; Jackson, 2015).

5. Conclusion

This chapter has explored equity in teacher education by integrating artificial intelligence (AI) within work-integrated learning (WIL). It argues that AI can act as a mediating tool that enhances access to meaningful, practice-based professional learning instead of replacing human pedagogical relationships. Drawing on connectivist and transformative learning theories, the chapter proposes a conceptual framework that positions teacher candidates within a networked learning ecology supported by AI-enabled tools. It defines equity in terms of both access to professional opportunities and the development of reflective, inclusive teaching practices. However, the chapter is conceptual in nature and, as such, is subject to certain limitations. The proposed framework has not yet been empirically validated, and its effectiveness has yet to be tested across diverse educational contexts. Moreover, the analysis relies on existing literature, which may not fully capture the rapidly evolving nature of AI technologies in education. The lack of context-specific case studies further limits the ability to address localised implementation challenges and cultural variations. Despite these limitations, the framework offers a theoretically grounded foundation for understanding how AI-mediated WIL can foster more equitable teacher education. Future research should focus on empirical validation, context-sensitive applications, and the long-term implications of AI integration for equity and professional learning. Through such efforts, AI-mediated WIL holds promise as a pathway toward more inclusive and transformative teacher education systems.

5.1 Recommendation

Based on the insights presented in this chapter, we propose several recommendations to promote the equitable implementation of AI-mediated work-integrated learning (WIL) in teacher education:

- Invest in Digital Infrastructure and Access: Teacher education institutions and policymakers should prioritise reliable internet connectivity, hardware provision, and access to AI-enabled tools, particularly for under-resourced and geographically isolated regions. Equitable access is fundamental to the success of AI-mediated WIL.
- Build Educator and Candidate Capacity: Continuous professional development for teacher educators and targeted digital literacy programmes for teacher candidates are essential to ensure effective engagement with AI-mediated supports, including learning analytics, virtual simulations, and adaptive feedback mechanisms.
- Promote Ethical and Inclusive AI Design: AI tools should be designed and implemented with attention to algorithmic fairness, cultural and linguistic responsiveness, and data privacy. Participatory design approaches involving teacher candidates, mentors, and local stakeholders can enhance relevance and inclusivity.
- Align AI Integration with Curriculum and Policy: AI should be embedded within existing curriculum structures, accreditation requirements, and institutional policies

rather than introduced as a standalone innovation. This alignment ensures that technology supports learning objectives, professional standards, and equity goals.

- Ensure Sustainability and Scalability: Institutions should adopt interoperable platforms, modular AI tools, and open educational resources that can be maintained and scaled across different contexts. Continuous monitoring, evaluation, and adaptive refinement are critical for long-term impact.
- Foster Reflective and Collaborative Practices: AI-mediated WIL should support reflective learning, peer collaboration, and mentoring relationships, reinforcing the social and dialogic dimensions of professional development highlighted by connectivist and transformative learning theories.

By implementing these recommendations, teacher education programmes can maximise the transformative potential of AI-mediated WIL while mitigating challenges that threaten equitable access and outcomes.

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CHAPTER FOUR

Beyond Access: Ensuring Equity in Digital Placements for Pre-Service Teachers' Work-Integrated Learning

Buhle Stella Nhlumayo

Department of Educational Foundations,

College of Education, University of South Africa, Pretoria, South Africa

Corresponding author: Buhle Stella Nhlumayo (nhlumbs@unisa.ac.za)

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Abstract: The incorporation of digital technologies in work-integrated learning (WIL) has become increasingly significant in teacher education, particularly in scenarios where traditional, face-to-face placements are restricted. While technology-mediated placements broaden accessibility and flexibility, they also raise crucial concerns regarding equity, inclusion, and participation for pre-service teachers. Guided by the Digital Equity Framework, this chapter conducts a critical analysis of existing literature to explore how equity can be upheld in digital WIL environments. The framework expands the concept of equity beyond technology access, encompassing aspects of meaningful participation, digital proficiency, and empowerment. Consequently, it offers a valuable perspective for investigating how the digital evolution in teacher education can foster not only connectivity but also agency and inclusion. Leveraging global and local academic work, the chapter examines how structural inequalities, digital discrepancies, and teaching methods influence the experiences of pre-service teachers in virtual placements. The discourse is structured around four interconnected themes: Access and Infrastructure, spotlighting the enduring disparities in connectivity and device provision; Digital Pedagogies and Support, evaluating fair mentoring and instructional design; Socioeconomic and Contextual Barriers, addressing inequalities associated with background and school environment; and Policy and Institutional Responses, delving into leadership, collaborations, and systemic transformation. The chapter asserts that progressing digital equity in WIL necessitates a holistic approach that aligns policy, leadership, and pedagogy to ensure that pre-service teachers are not just digitally connected but also empowered to excel within fair, technology-mediated professional learning settings.

Keywords: Digital equity, work-integrated learning, teacher education, educational leadership, policy and leadership.

1. Introduction

Work-integrated learning (WIL) is widely recognised as a cornerstone of teacher education, offering pre-service teachers structured opportunities to connect theoretical knowledge with professional practice. Through school-based placements, pre-service teachers develop pedagogical competence, professional identity, and contextual understanding of teaching and learning environments (du Plessis & Razmjoee, 2025). Traditionally, these placements have focused on face-to-face engagement within schools. However, recent shifts in educational provision, accelerated by technological advancements and disruptions such as the COVID-19 pandemic, have led to an increasing reliance on digitally mediated and hybrid WIL models. Short, Halton, Morris, Rose, Whitaker, Russ, Fitzroy, Appleton, Adamson, and Boyd (2023) argue that these developments have expanded placement access, flexibility, and continuity, especially in contexts where physical placements are limited by geography, capacity, or systemic disruption. While digital technologies have allowed teacher education institutions to sustain and, in some cases, enhance WIL opportunities, their rapid integration has also highlighted and, at times, exacerbated existing inequities within teacher education systems.

Emerging scholarship points to the growing role of artificial intelligence (AI) in shaping digitally mediated learning environments, including WIL. AI-driven tools are increasingly used for feedback, assessment, and instructional support, raising new questions about equity, access, and participation. Nzuza (2025) notes that access to devices, reliable connectivity, and appropriate digital platforms remains unevenly distributed, particularly for pre-service teachers from historically marginalised, rural, or low-income backgrounds. Additionally, Brown and Luo (2025) indicate that disparities in digital competence, institutional support, mentoring quality, and pedagogical design also affect the extent to which pre-service teachers can meaningfully engage in technology-mediated placements. Consequently, the expansion of digital WIL raises critical questions about equity, inclusion, and participation that go beyond the mere provision of technological infrastructure.

Emerging scholarship cautions against viewing digital WIL as a neutral or inherently equitable solution to placement challenges (Gamage, 2022; Bell, Bartimote, Dempsey, Mercer-Mapstone, Moran, & Tognolini, 2022). Instead, researchers emphasise the importance of examining how structural inequalities, socioeconomic conditions, and institutional practices intersect with digital modalities to influence pre-service teachers' learning experiences. In a study on inclusive placement learning for diverse higher education students, Thompson and Brewster (2023) indicate that without deliberate attention to equity, digital placements risk perpetuating patterns of exclusion, where some students benefit from flexibility and innovation, while others face barriers that hinder engagement, learning, and professional growth. These concerns highlight the necessity of moving beyond access-oriented approaches to consider equity as a multidimensional construct encompassing participation, capability, agency, and empowerment.

Global scholarship on digital work-integrated learning (WIL) and online teacher education highlights the transformative potential of technology to enhance access and flexibility, particularly in situations where physical placements are limited. Studies emphasise the role of digital platforms in facilitating continuity of professional learning, promoting new forms of collaboration, and supporting reflective practice (Cohen, DuBois, Lynch, Swami, Noftle & Arensberg, 2023; Manganello & Aleo, 2026). However, this body of work also reveals ongoing inequities in access to reliable connectivity, digital competence, and the quality of mentoring and instructional design. Concurrently, local South African literature underscores how these challenges are exacerbated by historical inequalities, socioeconomic disparities, and resource constraints within schools and higher education institutions (Nthambeleni & Motadi, 2025; Dlamini, 2022). Research in this context shows that pre-service teachers' experiences of digital placements are often influenced by unequal access to devices, limited institutional support, and diverse school environments that may not be adequately prepared for digital integration. Despite these findings, the literature lacks clarity on how equity can be systematically integrated into the design and implementation of digital placements, particularly through coordinated pedagogical, institutional, and policy interventions.

Drawing on both global and local scholarship, this chapter examines the conditions under which digital placements can support inclusive professional learning, as well as the policy, leadership, and pedagogical interventions necessary to ensure that pre-service teachers are not only connected to digital environments but also able to engage meaningfully and equitably within them. By situating digital WIL within broader discussions on equity and digital transformation in higher education, this chapter contributes to ongoing debates about how teacher education institutions can responsibly design, implement, and govern technology-mediated placements. In doing so, it aims to inform policy, institutional practices, and future research to advance equitable, inclusive, and empowering models of digital work-integrated learning.

2. Digital Work-Integrated Learning in Teacher Education

Work-integrated learning (WIL) in teacher education has traditionally been understood as face-to-face, school-based teaching practice where pre-service teachers develop professional competence through supervised classroom engagement (CHE, 2011; DHET, 2015). In South Africa and other Global South contexts, long-standing challenges such as uneven school resourcing, geographic disparities, and persistent inequalities in schooling systems have increasingly complicated the provision of equitable and high-quality WIL experiences (Maphumulo & Gcabashe, 2025; Nhlumayo & Mabeleng, 2025). In response to these challenges, digital placements have emerged as an alternative or complementary form of WIL, transforming how professional learning is conceptualised and implemented in teacher education. Digital work-integrated learning refers to structured teaching practice experiences where pre-service teachers engage in professional learning through online, virtual, or hybrid school environments (Schuster & Glavas, 2017). In this study, the authors use the term electronic work-integrated learning (eWIL) to describe this technology-facilitated form of WIL. In South African teacher education programmes, Czerniewicz (2018) notes that digital placements have included virtual lesson delivery, remote classroom observation, online assessment practices, and digital supervision by university lecturers and mentor teachers. These practices are common in Open Distance e-Learning (ODeL) institutions and align with national policy imperatives promoting digital transformation and innovation in higher education, including the DHET’s emphasis on integrating digital technologies into teaching and learning (DHET, 2020).

Literature from the Global South highlights that digital placements are often introduced in response to systemic constraints rather than as standalone pedagogical innovations. In South Africa, digital WIL has been influenced by stark inequalities in digital infrastructure between urban and rural schools, as well as disparities in connectivity, device access, and digital competence (Czerniewicz, 2018; Roberts & Hernandez, 2019). As a result, the quality and pedagogical depth of digital placements vary significantly across contexts, raising critical concerns about equity, comparability, and the legitimacy of digital WIL experiences (Bozalek, Ng'ambi & Gachago, 2013). The literature further distinguishes between emergency-driven digital placements, implemented to ensure continuity during periods of disruption, and intentionally designed digital WIL models that align with programme outcomes and are supported by structured mentoring and assessment (Kaqinari, Makarova, Audran, Döring, Göbel & Kern, 2022). In many Global South contexts, emergency approaches have prioritised access and participation, often at the expense of supervision quality, reflective practice, and contextual responsiveness. Luckett and Shay (2020) further reveal that purposefully designed models, in contrast, recognise digital placements as legitimate sites of professional learning that require dedicated frameworks, institutional investment, and policy support.

To conceptualise digital placements as WIL in South Africa, it is essential to understand teaching practice as a socio-contextual and digitally mediated process, shaped by institutional policies, school partnerships, and broader structural inequalities (CHE, 2011; DHET, 2015). This perspective positions digital WIL not merely as a technical solution to placement challenges but as a contested pedagogical space where issues of equity, professional identity, and educational justice are negotiated. Such a conceptualisation provides a critical foundation for examining how digital placements can either expand or constrain equitable participation in teacher education within South African and Global South contexts.

3. Theoretical Framework: The Digital Equity Framework

This chapter is grounded in the Digital Equity Framework (DEF), which provides a critical lens for examining the distribution of access to, use of, and benefits derived from digital technologies within educational systems. Moving beyond narrow understandings of digital equity as merely access to devices or connectivity, the framework emphasises the structural, pedagogical, and contextual conditions that shape meaningful participation in digitally mediated learning environments (Smith, 2021). This perspective is particularly pertinent to work-integrated learning (WIL) for pre-service teachers, where digital placements increasingly facilitate professional learning, supervision, and assessment.

Jackson, Starr, and Weaver (2024) conceptualise the DEF as a multidimensional construct encompassing technological access, digital skills and competencies, institutional support, and sociocultural and contextual factors. In the context of pre-service teachers' digital WIL placements, access refers not only to reliable devices and internet connectivity but also to equitable access to appropriate digital platforms, teaching resources, and virtual mentoring opportunities. Without these foundational conditions, participation in digital placements risks reproducing existing educational and socio-economic inequalities. Beyond access, the framework foregrounds capacity and capability, highlighting the importance of digital literacy, pedagogical readiness, and confidence in utilising digital tools for teaching and professional engagement. Pre-service teachers enter WIL placements with varied digital backgrounds, shaped by prior schooling, geographic location, and institutional resources, as noted by Rowston, Bower, and Woodcock (2022). The DEF, therefore, underscores how these disparities affect pre-service teachers' ability to engage meaningfully in digital teaching practices, collaborate with mentors, and demonstrate professional competence in online or hybrid environments. The framework further situates digital equity within institutional and systemic structures, including university policies, placement models, assessment practices, and support mechanisms. Equity in digital WIL placements depends on how institutions design placement requirements, provide training and technical support, and recognise the contextual constraints faced by both schools and student teachers (Lloyd, Paull, Clerke, & Male, 2019). From this perspective, inequities are not solely individual deficits but are produced and sustained through institutional arrangements and decision-making processes.

Finally, the DEF emphasises the importance of justice-oriented, inclusive pedagogical practices, advocating approaches that actively mitigate disadvantage rather than assuming uniform conditions of participation. Applied to this chapter, the framework enables a critical examination of how digital placements can either expand professional learning opportunities for pre-service teachers or exacerbate existing inequities if contextual realities are overlooked. By adopting the DEF as its theoretical lens, this chapter interrogates digital WIL placements not merely as innovative solutions to placement challenges, but as equity-laden practices that necessitate intentional design, institutional accountability, and sustained support to ensure fair and meaningful learning experiences for all pre-service teachers.

4. Discussion of Major Argument

While expanding access to digital platforms has been a central focus in the implementation of Work-Integrated Learning (WIL) for pre-service teachers, access alone does not guarantee meaningful or equitable participation. This chapter posits that achieving equity in digital placements necessitates a broader, more nuanced understanding of the structural, pedagogical, and contextual factors that shape students' experiences. It advances beyond a narrow focus on connectivity and devices to critically examine how inequalities are reproduced and can be addressed within digitally mediated WIL environments.

The discussion is organised around four key arguments. First, it highlights persistent gaps in access to reliable infrastructure and appropriate devices, which continue to disadvantage certain groups of students. Second, it examines the role of digital pedagogies and the extent to which mentoring and instructional design practices either enable or constrain equitable learning opportunities. Third, it considers the influence of socioeconomic and contextual factors, particularly how students' backgrounds and school placement contexts shape their engagement and success. Finally, the chapter explores policy and institutional responses, emphasising the need for leadership, strategic partnerships, and systemic reform to promote inclusive and equitable digital WIL practices. Collectively, these sections demonstrate that ensuring equity in digital placements requires coordinated efforts across multiple levels, moving beyond access towards more inclusive, responsive, and contextually grounded approaches.

4.1. Access and infrastructure: Persistent gaps in connectivity and device provision

Access to reliable digital infrastructure remains a foundational yet uneven condition for the successful implementation of digital placements in pre-service teachers' work-integrated learning (WIL). While digital and hybrid placement models have expanded opportunities for continuity in professional learning, particularly in contexts characterised by placement shortages or geographic constraints, Nzuza (2025) contends that persistent disparities in connectivity and device provision continue to influence who can meaningfully participate in these arrangements. This chapter posits that without addressing these structural inequities, digital WIL placements risk reproducing and, in some instances, intensifying existing educational inequalities. Connectivity remains one of the most significant barriers to equitable digital placements (Bell, Bartimote, Mercer-Mapstone, Moran, Tognolini, & Dempsey, 2021; Gunter, 2025). Furthermore, Abedi (2025) and Ndanu (2025) indicate that many pre-service teachers, particularly those from rural, peri-urban, and economically marginalised communities, experience unstable or limited internet access. Inconsistent bandwidth, high data costs, and frequent network disruptions constrain pre-service teachers' ability to participate in synchronous teaching sessions, engage in online mentoring, submit digital artefacts, and access learning management systems. These challenges are often exacerbated during school-based placements where partner schools themselves lack adequate connectivity, thereby limiting opportunities for authentic digital teaching practice and collaboration with mentors. Equally critical is the issue of device provision. Access to a personal, functional digital device cannot be assumed for all pre-service teachers. Some rely on shared household devices, outdated hardware, or mobile phones that are ill-suited for lesson planning, video-based teaching, or sustained engagement with digital platforms (Sharma, 2025). The absence of appropriate devices undermines the quality of professional learning experiences and imposes additional cognitive and emotional burdens on pre-service teachers, who must navigate technological constraints alongside the demands of teaching practice.

Institutional responses to these access challenges are often inconsistent. In their study on understanding the impact of the digital divide on South African students in higher education institutions, Faloye and Ajayi (2022) indicate that while some higher education institutions offer limited data packages, device loan schemes, or campus-based digital hubs, these interventions and the support provided are often insufficient, short-term, or inaccessible to students located far from university facilities. Moreover, Young, Harvey, and McKenzie (2024) argue that such support mechanisms tend to prioritise academic coursework over WIL-specific needs, leaving gaps in support during placement periods when digital engagement is most intensive.

From an equity perspective, access and infrastructure challenges must be understood as systemic rather than individual shortcomings. Particularly within the South African higher education context, pre-service teachers' capacity to succeed in digital WIL placements is shaped by broader socio-economic conditions, historical inequalities, and institutional resource allocation decisions (Msimango, 2025). Furthermore, Lutz (2019) indicates that inequity is no longer solely related to internet access, but also pertains to access to AI-enabled tools and platforms. Framing access issues as matters of individual responsibility obscures their structural nature and diverts attention away from the institutional accountability required to address these gaps. Ensuring equity in digital WIL placements, therefore, necessitates a deliberate and sustained investment in infrastructure that transcends baseline access. This includes partnerships with schools and service providers to enhance connectivity, scalable device provision strategies, and placement-sensitive support models that recognise the realities of students' learning environments (Aleksieva, 2025). Without such interventions, digital placements may, in principle, extend access while, in practice, limiting equity and reinforcing the very disparities they are intended to overcome.

From the Digital Equity Framework (DEF) perspective, the access and infrastructure challenges discussed in this section underscore that equity in digital WIL placements depends not only on the availability of connectivity and devices but also on the extent to which these resources facilitate meaningful participation and learning outcomes. The framework emphasises how uneven infrastructure, limited device access, and inconsistent institutional support systematically shape pre-service teachers' opportunities to engage in digitally mediated teaching and professional development. By situating connectivity and device provision within broader socio-economic and institutional contexts, the framework reinforces the need for structural, equity-driven responses that move beyond temporary fixes towards sustained investment and institutional accountability. In this way, access and infrastructure emerge as critical yet insufficient conditions for equity, highlighting the necessity to align digital WIL initiatives with fair principles that ensure all pre-service teachers can participate fully and benefit equitably from digital placements.

4.2 Digital pedagogies and support: Equity in mentoring and instructional design

While access to digital infrastructure is a necessary condition for participation in online or hybrid work-integrated learning (WIL) placements, it is not sufficient on its own to ensure equitable professional learning experiences for pre-service teachers. Equity in digital placements is also shaped by the quality of digital pedagogies, the nature of instructional design, and the availability of responsive mentoring and support structures (Ros, 2024). Moreover, Huang (2025) argues that equity encompasses who benefits from AI-supported pedagogy and who is left behind. This section examines how inequities in pedagogical practices and support systems influence pre-service teachers' engagement, learning, and professional development within digitally mediated WIL contexts.

Digital pedagogies in WIL settings require intentional design that acknowledges the complexities of teaching practice and the diverse contexts in which pre-service teachers are placed. However, Singh, Evans, Reed, Karch, Qualey, Singh, and Wiersma (2022) indicate that many digital placements and pedagogies rely on instructional designs that replicate traditional face-to-face supervision models without adequate adaptation to online environments. Such approaches often privilege pre-service teachers who already possess strong digital literacy, confidence in online communication, and familiarity with learning management systems. For others, particularly those from under-resourced schooling backgrounds, these designs can create additional barriers to participation and meaningful learning. In their study evaluating WIL using a context-sensitive approach, Young, Semple, Harvey, and McKenzie (2023) assert that equitable instructional design in digital WIL placements must be inclusive, flexible, and context-sensitive. This includes providing multimodal learning resources, clear expectations for digital engagement, and scaffolded opportunities for developing digital pedagogical competence. Asynchronous learning activities, recorded mentoring sessions, and varied assessment formats can support pre-service teachers facing connectivity challenges or balancing placement responsibilities with other socio-economic demands (Ersin & Atay, 2021). Such design choices acknowledge unequal starting points and aim to create fair conditions for learning rather than uniform experiences.

Furthermore, mentoring plays a critical role in shaping the quality of WIL experiences. However, James, Hudson, and Lasczik (2022) note that digital placements often reveal disparities in access to effective mentorship. In some contexts, mentor teachers and university supervisors lack the training or confidence to support pre-service teachers in online or hybrid teaching environments. This can result in inconsistent feedback, limited professional dialogue, and reduced opportunities for reflective practice. Pre-service teachers placed in digitally confident schools or supported by technologically adept mentors are thus advantaged, while others experience minimal guidance and professional isolation. An equity-oriented approach to digital mentoring necessitates structured, sustained, and well-supported mentoring models. This includes preparing mentor teachers and supervisors for digital supervision, clarifying roles and expectations, and providing platforms that facilitate regular, meaningful interaction. Moreover, Chan (2020) asserts that equitable mentoring also involves recognising power dynamics within digital spaces and ensuring that pre-service teachers' voices, challenges, and contextual realities are acknowledged and addressed.

Institutional support mechanisms significantly influence the effectiveness of digital pedagogies and mentoring. Essential components such as technical help desks, pedagogical support teams, and professional development initiatives for both mentors and pre-service teachers are crucial for promoting equitable engagement (Nzuza, 2025). When such support is fragmented or reactive, inequities are likely to persist, placing the burden of adaptation on individual students rather than on the institutions themselves. In summary, digital pedagogies and support structures are vital for ensuring equity in digital WIL placements. Beyond merely providing access, institutions must invest in inclusive instructional design and equitable mentoring practices that acknowledge diversity in digital readiness and contextual constraints. Only through intentional, justice-oriented approaches can digital placements realise their potential to expand, rather than limit, professional learning opportunities for pre-service teachers.

4.3. Socioeconomic and contextual barriers: Disparities linked to background and school context

Equity in digital work-integrated learning (WIL) placements for pre-service teachers is significantly influenced by socioeconomic and contextual factors that go beyond mere access to technology and institutional support. The social, economic, and geographic backgrounds of students, alongside the contexts of the schools in which they are placed, play a crucial role in determining their ability to engage meaningfully in digitally mediated professional learning (Salisu, Al-Mamary, Alfalah, Abubakar, Al-Samhi, Goaill, Alhaidan & Alshammari, 2026). This section explores how these intersecting factors contribute to uneven experiences and outcomes in digital WIL placements.

Pre-service teachers enter WIL placements with diverse socioeconomic realities that affect their engagement with digital learning environments. As mentioned earlier in this chapter, students from economically disadvantaged backgrounds often encounter constraints such as limited financial resources for data, unstable living conditions, and competing responsibilities, including paid work or caregiving, particularly for those in ODeL institutions. A study by Jan and Mahboob (2022) on the challenges and strategies of online mentoring highlights how these factors can restrict the time, focus, and flexibility needed to fully participate in online mentoring sessions, synchronous teaching activities, or extended digital lesson preparation. In contrast, students from more privileged backgrounds are generally more likely to have access to stable learning environments and supplementary resources that facilitate sustained engagement. The potential for AI to reproduce privilege arises if only certain students can effectively leverage it (Cao, Choi, Park & Lee, 2025). Geographic contexts further exacerbate these disparities. Pre-service teachers placed in rural or remote areas often face challenges such as weaker digital infrastructure, limited technical support, and reduced exposure to technology-enhanced teaching practices (Nhlumayo, 2024). Additionally, Kormos and Wisdom (2021) note that schools in these contexts may lack learning management systems, digital teaching tools, or adequately trained personnel to support online instruction. Consequently, digital placements may become more symbolic than substantive, providing limited opportunities for genuine engagement with digital pedagogies or professional collaboration.

The context of the school also plays a vital role in shaping equity within digital WIL experiences. Well-resourced schools with robust digital cultures tend to offer structured support, mentorship, and opportunities for innovation, which enhance pre-service teachers' professional learning (Msimango, 2025). In contrast, Ajani and Govender (2025) observe that under-resourced schools often prioritise basic instructional continuity over digital experimentation, which limits pre-service teachers' exposure to meaningful technology integration. These contextual differences can inadvertently favour some students while marginalising others, thereby reinforcing pre-existing inequalities within teacher education pathways. A study by Chhabra (2021) on pre-service teachers' habitus and meaning-making processes in diverse classroom placements when teaching and engaging with technology for equity suggests that cultural and social capital further influence how pre-service teachers navigate digital placements. Familiarity with academic discourse, professional communication norms, and digital platforms is not evenly distributed and is often linked to prior educational experiences. Students who lack this capital may experience heightened anxiety, reduced confidence, and limited participation in online professional spaces. Without targeted support, digital placements may amplify these hidden inequities, framing challenges as individual shortcomings rather than contextual constraints.

From an equity perspective, socioeconomic and contextual barriers must be recognised as structural conditions that shape digital WIL experiences. Addressing these disparities necessitates institutional strategies that are sensitive to students' lived realities and the diverse contexts of partner schools. This encompasses flexible placement models, differentiated support mechanisms, and stronger partnerships with schools in under-resourced communities. Ultimately, ensuring equity in digital WIL placements demands an approach that accounts for the complex interplay between socioeconomic background and school context. By foregrounding these factors, institutions can move beyond deficit-based interpretations of student performance and towards more just, inclusive, and context-responsive models of professional learning for pre-service teachers (Sha, Xiaoxiao, Li & Wenmeng, 2025; Destiny & Lator, 2024). Viewed through the Digital Equity Framework, the disparities outlined in this section underscore that equity in digital WIL placements cannot be reduced to questions of access alone, but must be understood in relation to students' capabilities, opportunities for meaningful participation, and the outcomes of their professional learning experiences. The framework foregrounds how socioeconomic background, geographic location, school context, and forms of social and cultural capital interact to shape pre-service teachers' engagement with digitally mediated WIL. By situating these challenges within broader structural and institutional contexts, the Digital Equity Framework shifts the focus from individual deficits to systemic responsibility. It provides a coherent theoretical foundation for this chapter by highlighting the need for context-responsive, justice-oriented interventions that address not only technological provision but also pedagogical support, institutional partnerships, and differentiated forms of assistance. In doing so, the framework reinforces the chapter's central argument: that ensuring equity in digital placements requires intentional, systemic approaches that enable all pre-service teachers to participate meaningfully and benefit equitably from work-integrated learning in digital contexts.

4.4 Policy and institutional responses: Leadership, partnerships, and systemic reform

Ensuring equity in digital work-integrated learning (WIL) placements for pre-service teachers necessitates deliberate, coordinated policy and institutional responses that extend beyond ad hoc and informal solutions. While digital placements have emerged as a practical response to placement shortages and disruptions, their long-term viability and equity hinge on strong leadership, collaborative partnerships, and systemic reform. This section explores how institutional policies and leadership practices can either promote or hinder equitable digital WIL experiences.

Saad, Alias, Chong, and Sabri (2025) and Zabalawi, Kordahji, and Aftimos (2024) suggest that leadership at the institutional level plays a central role in shaping the vision, priorities, and funding for digital WIL initiatives. The authors further indicate that higher education institutions should foster a digitally and equity-transformed educational environment. Equity-oriented leadership involves recognising digital placements as pedagogical spaces that require the same level of planning, quality assurance, and support as traditional school-based placements. However, in many contexts, digital WIL policies remain underdeveloped or are viewed as temporary alternatives rather than integral components of teacher education programmes (Msila, 2025). This lack of formal policy direction often results in inconsistent implementation, unclear expectations for students and mentors, and uneven access to support. Effective policy responses require clear guidelines defining the purpose, scope, and standards of digital WIL placements. Such policies should address issues of access, mentoring, assessment, workload, and ethical use of digital technologies. Importantly, equity considerations must be embedded within these frameworks to ensure that institutional responses are sensitive to students' diverse contexts and do not assume uniform conditions of participation.

Partnerships and stakeholder collaboration between universities, schools, and external stakeholders are equally critical in advancing equitable digital education and placements (Siddiqi, 2024). Strong and reciprocal partnerships enable shared responsibility for mentoring, resource provision, and professional learning. Letuma and Dlamini (2025) state that schools serve as key sites of practice, while universities provide pedagogical guidance, supervision, and infrastructure support. In digitally constrained contexts, partnerships with government departments, non-governmental organisations (Djatmiko, Sinaga & Pawirosumarto, 2025), and technology providers can help address gaps in connectivity, device access, and training. Without such collaboration, digital WIL initiatives risk imposing disproportionate burdens on individual schools or pre-service teachers.

Systemic reform is essential to address the structural conditions that perpetuate inequities in digital WIL placements. This necessitates a re-evaluation of placement models to permit flexibility, hybrid approaches, and differentiated support based on contextual realities. Additionally, it involves investing in professional development for university supervisors and mentor teachers to enhance their capacity for digital mentoring and assessment. Systemic reform further requires the alignment of digital WIL policies with broader institutional strategies regarding digital transformation, teacher education, and social justice. Accountability mechanisms are crucial for sustaining equitable practices. Institutions must establish processes for monitoring the quality and equity of digital placements, including mechanisms for student feedback, data-driven evaluation, and continuous improvement. Moreover, Calzada and Eizaguirre (2025) advocate for a transition from digital inclusion to AI inclusion and governance. Equity indicators should be integrated into programme review and accreditation processes to ensure that digital WIL initiatives are not only innovative but also just and inclusive.

The DEF emphasises that equitable digital participation is shaped by institutional rules, norms, resource distribution, and power relations, all of which are enacted through leadership decisions, policy design, and partnership structures. From this perspective, leadership commitment, coherent policy frameworks, and accountable partnerships are pivotal to enabling fair access, meaningful participation, and equitable outcomes in digital WIL placements. Thus, the framework reinforces the assertion that sustainable equity in digital WIL cannot be attained through individual efforts alone; it necessitates coordinated institutional action, systemic reform, and ongoing accountability to ensure that digital placements function as inclusive and just environments for professional learning. In conclusion, policy and institutional responses to digital WIL placements must be grounded in robust leadership, collaborative partnerships, and a commitment to systemic reform. By embedding equity at the centre of policy design and implementation, institutions can transform digital placements from short-term solutions into sustainable, inclusive models of professional learning that support diverse pre-service teachers and enhance teacher education systems.

5. Conclusion

This chapter critically examines equity in digital work-integrated learning (WIL) placements for pre-service teachers, arguing that while access to digital technologies is necessary, it is insufficient to ensure equitable professional learning experiences. Drawing on the Digital Equity Framework, the review demonstrates that equity in digital placements is influenced by a complex interaction of infrastructure, pedagogical support, socioeconomic background, institutional policy, and school context. Consequently, digital placements do not function as neutral or universally beneficial innovations; rather, they serve as pedagogical spaces that can either mitigate or reproduce longstanding inequalities in teacher education. The literature reviewed reveals persistent gaps in connectivity and device provision, uneven mentoring and pedagogical support, and significant disparities linked to students' socioeconomic backgrounds and placement contexts. In South African and broader Global South settings, these challenges are exacerbated by historical patterns of inequality and varying institutional capacity. While digital

WIL placements have the potential to expand access and alleviate placement shortages, this chapter illustrates that without intentional design and systemic support, such models risk favouring students and schools that are already digitally resourced.

The chapter further emphasises the critical role of institutional leadership, policy coherence, and partnerships in promoting equity in digital WIL. Effective responses require a shift away from short-term, emergency-driven solutions towards sustainable, equity-oriented frameworks that recognise digital placements as legitimate and complex sites of professional learning. This includes investing in infrastructure, enhancing mentor capacity, embedding ethical and inclusive pedagogical practices, and developing accountability mechanisms that prioritise equity outcomes. By applying the Digital Equity Framework as a cohesive theoretical lens, the chapter offers a structured approach to understanding how equity can be operationalised in digital WIL placements. It advocates for a transition from access-focused narratives to justice-oriented practices that address participation, capability development, and learning outcomes. Ultimately, ensuring equity in digital placements requires coordinated institutional action and ongoing critical reflection, positioning digital WIL not merely as a response to constraints, but as an opportunity to envision more inclusive and socially just models of teacher professional learning.

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CHAPTER FIVE

Integrating Artificial Intelligence in African Pedagogies for Learning in Educational Management

Ohunene Florence Omuya

Department of Educational Foundations,

Faculty of Education, Federal University Lokoja, Kogi State, Nigeria

Oluwatosin Motunrayo Kachi

Department of Educational Management,

Faculty of Education, Federal University Lokoja, Kogi State, Nigeria

Corresponding author: Oluwatosin Motunrayo Kachi (oluwatosin.kachi@fulokoja.edu.ng)

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Abstract: The integration of Artificial Intelligence into African pedagogies within educational management is a welcome idea for transforming teaching, learning, and administrative processes in the educational system. This study focuses on the role of artificial intelligence in African pedagogical innovations to promote institutional efficiency and effectiveness, anchored in the theories of innovation diffusion and digital transformation. The research employed a descriptive research design involving principals, teachers, and supervisors in public secondary schools across the three senatorial zones of Kogi State, Nigeria. A structured questionnaire was used to elicit information from the respondents. The population included all principals, supervisors, and teachers from 300 schools in 21 Local Government Areas of Kogi State, Nigeria. Simple random sampling techniques were used to select 100 schools from 10 Local Government Areas. A stratified random sampling technique was employed to select a sample size of 500, which included 100 principals, 350 teachers, and 50 supervisors. The study is quantitative in approach. The validity of the instrument was determined by experts in the field of measurement and evaluation using content validity, and Cronbach's Alpha was used to assess the reliability of the instrument, resulting in a value of 0.85 at the 0.05 level of significance. The data collected were analysed using descriptive statistics (simple percentage), and Analysis of Variance (ANOVA) was used to test the hypotheses at the 0.05 level of significance. The findings revealed that the integration of artificial intelligence into storytelling encourages creativity and the right imagination among students, aligning with the 21st century. Additionally, the findings showed that the integration of artificial intelligence will help prepare students for lifelong learning that enhances their critical thinking. The study concludes that the integration of artificial intelligence in educational management demands strategic government policy support for professional capacity building and sustainable investment in digital infrastructure that will promote African indigenous pedagogies. The study recommends that the government should invest in stable internet connectivity, smart classrooms, and AI-powered learning management systems.

Keywords: Integrating, artificial intelligence, pedagogies, learning, educational management.

1. Introduction

Educational management encompasses curriculum design, teacher professional development, resource allocation, institutional leadership, and governance, all of which play a vital role in shaping the quality of teaching and learning. The significance of educational management includes efficient resource utilisation, policy implementation, quality assurance, improved teaching and learning, as well as innovation and change management. Educational management has a crucial role in the integration of artificial intelligence (AI) into African indigenous pedagogies. The advent of AI presents new opportunities for pedagogies that utilise technology to enhance teaching and learning. There is a growing body of systemic reviews indicating that AI in education has progressed beyond isolated tools to holistic systems (Baker & Hawn, 2021). Another review by Adewale (2023) highlights that AI is fundamentally reshaping pedagogical relationships and processes, such as the transition from a teacher-centred to a learner-centred approach. However, the review conducted by Baliton (2023) demonstrates that AI can also be employed to support administrative platforms, personalised services, and evidence-based decision-making. Furthermore, the use of AI in educational management to promote African indigenous pedagogies will contribute to the strengthening of student-centred learning. The integration of AI into education has become imperative, extending beyond classroom teaching to encompass the realm of educational management.The relationship between educational management, African indigenous pedagogies, and AI is transformative and strategic, as AI serves as a tool to preserve knowledge, personalise learning, and bridge traditional and modern pedagogies (Baker & Hawn, 2021). Baker and Hawn (2021) assert that educational managers determine how AI can be adopted, how it is utilised, and how to map out strategic planning and implementation with ethical considerations to regulate the use of AI.In a similar vein, Okeke (2021) argues that the effectiveness of AI in African education is contingent upon the degree to which it is embedded within educational management systems and aligned with indigenous African pedagogical philosophies.

The 21st century demands new approaches to learning that leverage AI to foster critical creativity, collaboration, and adaptability. According to Adewale (2023), educational reforms must incorporate AI into pedagogies that offer valuable insights rooted in centuries of practical experience. He concludes that these pedagogies are inherently learner-centred, experiential, and community-oriented, aligning with modern educational objectives. Tabulawa (2013) posits that pedagogies are methods employed to enhance teaching and learning. Traditional methods and philosophies of teaching and learning that have developed within African communities include storytelling, apprenticeship, observation, oral transmission, song, dance, proverbs, communal responsibility, and spiritual guidance. Similarly, Adewumi (2022) examines African indigenous pedagogies as forms of learning that often occur through active participation, mentorship, and social interaction, aiming to develop moral character, social responsibility, and practical skills. Kumar and Bawa (2021) enumerate the core features of African indigenous pedagogies as follows: community-centred learning, which involves education as a collective responsibility engaging elders, family members, and community leaders; morality and storytelling, which entails transmitting knowledge through oral narratives that promote memory, ethics, and imagination; learning by doing, where skills are acquired through observation, imitation, and practice rather than passive instruction; holistic development, which emphasises the development of the whole person—intellectually, morally, spiritually, and socially; and contextual relevance, where learning is grounded in local culture, environment, and practical life experiences.

Matthew (2020) opined that African indigenous pedagogies are traditional methods of teaching and learning that have evolved over centuries through oral transmission, observation, participation, and apprenticeship. These pedagogies are closely knit with cultural practices, social norms, and environmental contexts. However, Akinyemi (2021) emphasised that 21st-century learning centres on critical thinking, creativity, communication, and digital literacy; many of these modern competencies are already inherent in indigenous African learning systems. For instance, storytelling is not merely a means of entertainment but a pedagogical tool that develops imagination, critical analysis, and moral reasoning.

UNESCO (2019) advocated for the integration of indigenous knowledge into formal curricula to render education more relevant, inclusive, and sustainable. The appropriate application of African indigenous pedagogies bridges the gap between home culture and school, thus enhancing learner engagement and achievement. In the same vein, UNESCO (2019) emphasised that the 21st century requires the following: critical thinking, which involves elements such as proverbs and storytelling that foster analytical thinking and ethical reasoning; collaboration, encompassing communal activities like farming, ceremonies, and decision-making to inculcate teamwork and shared responsibility; creativity, manifested in oral literature, music, and dance to encourage imagination and self-expression; and lifelong learning, wherein indigenous systems regard learning as a continuous process throughout life, not confined to classrooms.

Recent research calls for a paradigm shift that values both indigenous and modern pedagogical approaches. Curriculum reforms in countries like Kenya, Ghana, and South Africa are beginning to acknowledge the necessity for culturally responsive education through the integration of artificial intelligence (Tabulawa, 2013). This initiative aims to incorporate artificial intelligence into local content using mother tongue instruction in early grades. In Nigeria, the curriculum was redesigned to accommodate mother tongue as a mode of learning in primary schools nationwide to enhance the effectiveness and efficiency of learning pedagogies. However, research conducted by David (2025) advocated for integrative pedagogies using artificial intelligence that respect both indigenous wisdom and scientific inquiry, fostering learners who are globally competent yet locally rooted. This hybrid approach enhances the adaptability of education systems and strengthens cultural identity among learners.

Baliton (2023) asserted that digital tools present new opportunities for preserving and disseminating oral traditions, stories, and proverbs in interactive and accessible formats. In this same vein, Odora (2021) opined that there is global recognition of indigenous knowledge in contributing to sustainability, peace education, and holistic learning. The 2030 Sustainable Development Goals (SDGs), particularly SDG 4 on inclusive and quality education, call for the recognition of diverse knowledge systems. In this context, African indigenous pedagogies provide rich, context-sensitive learning models that challenge the dominance of Western paradigms in knowledge production. Embracing these pedagogies and integrating them with emerging technologies such as artificial intelligence will not only revitalise African education but also contribute to the enrichment of global educational thought and practice.

Olugbenga (2024) examined the concept of pedagogy as the strategies, methods, and approaches employed in the teaching and learning process. He emphasised that the 21st-century pedagogies in Africa, especially in educational institutions in Nigeria, suffer setbacks due to technological barriers, insufficient teacher training and professional development, and limited resources. However, he suggested that policy reforms, teacher training and professional development, technology integration, partnerships, research, and monitoring are ways to improve the utilisation of 21st-century pedagogies in alignment with African indigenous pedagogies through the integration of artificial intelligence. Peter and Adewale (2025) argued that innovative pedagogies in Africa must be promoted. They stressed that all children are active learners with an equal right to learn. Therefore, learning should be participatory, enjoyable, and adapted to the developmental needs of each learner. In Africa, the innovative pedagogies project advocates the introduction of inclusive, participatory, and adaptive pedagogies within school systems.

Several studies, for example, Muraina et al. (2025), emphasised that AI supports teaching and learning by extending support for management-oriented pedagogies and also helps in innovative pedagogies that promote effective learning. The findings of a study conducted by Adebayo and Ojo (2021) demonstrated that indigenous pedagogies can align with 21st-century learning paradigms, such as storytelling, which encourages creativity and imagination among students through the use of artificial intelligence. This aligns with Matthew (2020), who asserted that pedagogies that occur through active participation, mentorship, and social interaction, aimed at developing moral character, social responsibility, and practical skills, can enhance collaboration skills and critical thinking among students through the use of artificial intelligence.

Integrating AI into indigenous methods assists students in applying knowledge to real-life situations. This assertion is supported by Akinyemi (2021), who posits that 21st-century learning centres on critical thinking, creativity, communication, and digital literacy—attributes that are already inherent in indigenous African learning systems. Ogunleye (2022) conducted a study titled "Artificial Intelligence in Teacher Education" and revealed that AI pedagogies, such as intelligent learning systems, data analytics for performance monitoring, and automated administrative processes, significantly enhance instructional delivery in African pedagogies

(Muraina & 2025). Adewumi (2022) further supports this perspective, noting that while indigenous pedagogies possess qualities that align with 21st-century learning through the utilisation of Artificial Intelligence, the integration of these methods into the curriculum relies on systemic general acceptance and training among stakeholders. This is reinforced by socio-cultural theory, which emphasises the influence of cultural context on teaching and learning. Similar studies by Ogunyemi and Henning (2021) indicate that grassroots educators tend to favour indigenous pedagogies over those preferred by administrators, as they promote collaborative skills through communal activities and foster critical thinking through oral storytelling and proverbs.

The gap between these pedagogies and current educational practices lies in the disconnection of teaching methods in schools from students' cultural and social realities, coupled with the limited integration of local content into the formal education system, as well as the underrepresentation of indigenous knowledge in AI systems. However, this study is founded on Rogers' innovation diffusion theory, which identifies five major components: innovation, communication channels, time, social systems, and adopter categories. The implications of this theory for the study lie in its ability to explain how teachers adopt new pedagogies and assist educational managers in planning implementation strategies. Digital theory encompasses the integration of digital technology into every aspect of an organisation. It comprises four components: technology integration, organisational change, cultural shift, and user focus. The implications for this study highlight its support for e-learning and driven instruction, thereby facilitating the integration of indigenous knowledge through digital platforms (Westermann, Bonnet, & McAfee, 2014).

1.1 Problem Statement

Despite global shifts in education towards inclusive, culturally responsive, and skills-based learning for the 21st Century, African indigenous pedagogies remain marginalised within formal education systems. The gap between traditional African teaching methods, such as storytelling and communal learning, and contemporary educational practices highlights a practical experience that is inherently learner-centred, experiential, and value-driven. These approaches align with 21st Century Competencies, including creativity, critical thinking, collaboration, and adaptability. However, inNigeria, African educational systems heavily rely on Eurocentric models that often neglect the socio-cultural realities pertinent to African learners. The dominance of colonial languages and standardised instruction limits the potential of education to be relevant, transformative, and empowering (Adebayo & Ojo, 2021). This disconnection contributes to poor learner engagement, cultural alienation, and a missed opportunity to harness Africa's rich intellectual heritage for educational innovation. Therefore, this study evaluates how African indigenous pedagogies, with a focus on Kogi State, Nigeria, can be meaningfully integrated into a modern educational framework in the 21st Century to enhance learning outcomes and cultural relevance. However, despite the growing adoption of Artificial Intelligence,the Kogi State school system still struggles with the effective integration of technology into teaching and learning processes. While AI can enhance instructional delivery, personalise learning, and improve management efficiency, its integration into African pedagogies, particularly indigenous community-based teaching methods, remains limited and poorly understood. Hence, there is a need to explore how Artificial Intelligence can be effectively integrated into African indigenous pedagogies through educational management in secondary schools in Kogi State.

1.1.1 Research questions

The following questions are sought to guide the study:

- To what extent does integration of artificial intelligence in indigenous pedagogies align with 21st century in Secondary schools in Kogi State, Nigeria?
- What are the perceptions of stakeholders in education in integrating artificial intelligence in indigenous pedagogies for classroom instructions in Secondary Schools in Kogi State, Nigeria?

1.1.2 Research hypotheses

The following null hypotheses are formulated to guide the study:

- H_{01}: There is no significant difference in the perception of Principals, Teachers and Supervisors regarding integration of artificial intelligence in indigenous pedagogies and alignment with 21st century learning in Secondary Schools in Kogi State, Nigeria.
- H_{02}: There is no significant difference in the perception of Principals, Teachers, and Supervisors regarding integrating artificial intelligent on indigenous Pedagogies for classroom instructions in Secondary Schools in Kogi State, Nigeria.

2. Methodology

The study adopted a descriptive survey design, and the population consisted of public secondary schools in Kogi State, Nigeria. The total population was 3,700, which included 500 principals, 3,000 teachers, and 200 supervisors.The sample size was determined using stratified random sampling, distributing the samples into strata based on profession. A sample size of 500 was obtained, consisting of 100 principals, 350 teachers, and 50 supervisors from the three educational zones in Kogi State. Simple random sampling techniques were used to select 100 public schools from 10 local government areas out of the 21 local government areas.

The instrument used was structured questionnaires with a 4-point Likert scale of strongly agree, agree, disagree, and strongly disagree. The instrument was validated by experts in the field of educational measurement and evaluation, and a reliability coefficient of 0.85 was obtained using Cronbach's Alpha at a 0.05 significance level. The data collected for the research questions were analysed using simple percentages, while the null hypotheses were assessed using Analysis of Variance (ANOVA) at the 0.05 level of significance.

3. Presentation of Results

This section presents the answers to the research questions as outlined in Tables 1 and 2, using simple percentages with a modified Likert scale. Table 3 analyses Null Hypothesis 1 using ANOVA, Table 4 presents the post hoc analysis to show the differences in opinions among principals, teachers, and supervisors, and Table 5 analyses Null Hypothesis 2, also using ANOVA. The following table answers Research Question 1 on Indigenous Pedagogies and 21st Century Learning Skills.

Table 1: *Indigenous pedagogies and 21st century learning skills*

S/N	Item Statement	Categories of respondents	SA	A	D	SD
1.	Integration of Artificial intelligence into storytelling encourages creativity and imagination among students	Principals Teachers Supervisors	50 (50%) 200 (57.14%) 30(60%)	30(30%) 80(22.85%) 20(40%)	20 (20%) 20(5.71%)	- 50(14.29%)
2.	Integrating artificial intelligence into Communal learning activities help students develop collaboration skills.	Principals Teachers Supervisors	60 (60%) 140(40%) 20(40%)	10 (10%) 160(45.71%) 10(20%)	30 (30%) - 20(40%)	— 50(14.29%)
3.	Using of artificial intelligence for Proverbs and oral narratives promote critical thinking and moral reasoning among students.	Principals Teachers Supervisors	70 (70%) 190(54.29%) 50(100 %)	30 (30%) 100(28.57%) -	- 60(17.14%) -	- -
4.	Integrating artificial intelligence in Indigenous methods help students apply knowledge to real-life situations.	Principals Teachers Supervisors	60(60%) 150(42.86%) 30(60%)	30 (30%) 200(57.14%) -	10 (10%) - 20(40%)	- - -
5.	Integrating artificial intelligence on Learning by going through apprenticeship	Principals Teachers Supervisors	20(20%) 100(28.57%) 20(40%)	30 (30%) 80(22.86%) 10(20%)	50(50%) 120(34.28%) 20(40%)	- 50(14.29%) -

	prepares students for lifelong learning.					

Item statement 1 shows that the integration of storytelling encourages creativity and imagination among students, with 50 principals representing 50% strongly agreeing, and 30 principals (30%) agreeing, respectively. Meanwhile, 20 principals, representing 20%, disagreed with the item statement. However, 200 teachers, representing 57.14%, strongly agreed, and 80 teachers (22.85%) agreed with the statement, although 20 teachers (5.71%) disagreed and 50 (14.29%) strongly disagreed. Additionally, 30 supervisors, representing 60%, strongly agreed, while 20 (40%) agreed, respectively. Invariably, all the respondents (principals, teachers, and supervisors) believe that if AI is integrated into storytelling, it will enhance students' ability to be creative.

Item statement 2 indicates that integrating AI into communal learning activities helps students develop collaboration skills, with 60 principals (60%) strongly agreeing with the statement and 10% agreeing, while 30 (30%) disagreed. Both teachers and supervisors positively affirmed this, with over 40% strongly agreeing and agreeing, respectively, showcasing strong support for the integration of artificial intelligence. In response to item statements 3 to 5, regarding the use of artificial intelligence for proverbs and oral narratives to promote critical thinkingand moral reasoning,the integration of AI into indigenous methods to help students apply knowledge to real-life situations, and the use of AI in learning through apprenticeship to effectively prepare students for lifelong learning, principals, teachers, and supervisors responded positively, with percentages of those who strongly agreed and agreed reaching up to60%. However, 40% of the teachersand supervisors expressed negative responses, as they both disagreed with the statements. Invariably, the perceptions of principals, teachers, and supervisors differ in their responses to item statements 3 to 5.

The following is the answer to Research Question 2 on perceptions of the integration of artificial intelligence.

Table 2: *Perceptions toward integration of artificial intelligence*

S/N	Item Statement	Categories of respondents	SA	A	D	SD
6.	Artificial intelligence should be integrated into the school curriculum for the teaching of indigenous pedagogies	Principals Teachers Supervisors	50(50%) 200(57.14%) 30(60%)	20(20%) 80(22.86%) 20(40%)	30(30%) 20(5.72%)	- 50(14.28%)
7.	Teaching in local languages using artificial intelligence enhances learners' understanding in lower primary	Principals Teachers Supervisors	30(30%) 80(22.86%) 30(60%)	- 20(5.72%) 20(40%)	70(70%) 150(42.86%)	— 100(28.58%)

8.	Blended Indigenous and modern pedagogies through artificial intelligence improve student's learning outcome	Principals Teachers Supervisors	60(60%) 200(57.14%) 50(100%)	40(40%) 50(14.28%) -	- 100(28.58%) -	- - -
9.	Indigenous pedagogies are outdated and should not be part of modern education of using technology such as artificial intelligence.	Principals Teachers Supervisors	30(30%) 60(17.14%) -	- 40(11.42%) -	70(70%) 100(28.58%) 30(60%)	- 150(42.86%) 20(40%)
10.	Indigenous pedagogies using artificial intelligence will contribute to mass failure if included in the curriculum	Principals Teachers Supervisors	70(70%) 200(57.14%) -	- 100(28.58%) 50(100%)	30(30%) 50(14.28%)	- -

Data from Table 2 revealed that for item 6, both principals, teachers, and supervisors had between 40% and 60% strongly agreeing with the item statement, while 5.72% to 30% disagreed, indicating that they were not in support of integrating AI into the school curriculum. However, itemstatement 7 showed that the responses from principals and teachers were negative, with 28.58% to 70% disagreeing, which suggests that the integration of AI in the junior class will not enhance students' understanding. In contrast, 40% to 60% of supervisorsresponded positively, indicating that supervisors from the ministrysolely support the notion that integrating AI will help improve students' ability to understand concepts being taught. Items 8 and 10 revealed that the responses from principals, teachers, and supervisors were affirmatively positive, recording the highest percentage range of 57.14% to 100%. Conversely, item statement 9 indicated that principals, teachers, and supervisors all responded negatively, disagreeing with the item statement at rates of 28.58% to 70%, respectively. This demonstrates that principals, teachers, and supervisors have diverse opinions regarding the item statement. The following table 3 responds to hypothesis 1.

***Table 3**: H_{01} No significant difference on indigenous pedagogies and 21st century learning using ANOVA*

Source of Variation	**SS**	**Df**	**MS**	**F**	**P – Value**
Between Groups	117.12	2	58.56	1457.22	< 0.001
Within Groups	20.08	498	0.0404		
Total	137.20	500			

From Table 3, the calculated F value is very high at 145.22, and the P-value is <0.001 at the 0.05 level of significance. This indicates that the null hypothesis is rejected, as there are differences among teachers, principals, and supervisors. This result was subjected to Tukey's HSD post hoc analysis to obtain the mean differences and their P-values.

Table 4: Post HOC analysis

Groups	Mean Difference	P- Value	Interpretation
Teachers vs Supervisors	0.052	<0.001	Significant difference
Teachers vs Principals	1.34	<0.001	Significant difference
Principals vs Supervisors	0.91	<0.001	Significant difference

This table shows the significant differences among the perceptions of principals, teachers, and supervisors regarding the integration of Artificial Intelligence into African pedagogies to align with 21st-century learning. The following table 5 responds to hypothesis 2.

***Table 5**: H_{02} No significant difference on integration of indigenous pedagogies on classroom instruction*

Source of Variation	SS	Df	MS	F	P - Value
Between Groups	86.445	2	43.223	1.60	P>0.05
Within Groups	13440	498	26.99		
Total	13526.445	500			

There is no statistically significant difference among principals, teachers, and supervisors, as F is 1.60 and $P > 0.05$; therefore, the null hypothesis is accepted.

4. Discussion of Findings

The analysis of data collected from all the item statements was examined during the research, revealing several findings. These findings are quite instructive and worth embracing. Firstly, the study revealed that the integration of artificial intelligence into storytelling encourages creativity and imagination among students, aligning with 21st-century learning. This is in line with Akinyemi's (2021) assertion that 21st-century learning should centre on critical thinking, creativity, communication, and digital literacy, which are inherent in the indigenous African learning system. The study also found that integrating artificial intelligence into 21st-century education will not only enhance pedagogies but also help students develop collaborative skills necessary for AI-driven pedagogies, such as intelligent learning systems, data analytics for performance monitoring, and automated administrative processes, significantly improving instructional delivery in African pedagogies. This is supported by Adewumi's (2022) perspective that, while indigenous pedagogies possess qualities aligning with 21st-century learning, the integration of AI into the curriculum relies on systemic general acceptance and training among stakeholders. This contradicts Marine's (2019) findings that artificial intelligence should not be integrated into African pedagogies, as this would undermine the value of the African system of learning.

Secondly, the findings showed that the integration of artificial intelligence would help prepare students for lifelong learning and enhance their critical thinking. This affirms Okonkwo and

Eze's (2020)observation that traditional pedagogical approaches in Nigeria often follow a one-size-fits-all model, which may not address the diverse needs of students, whereas AI-driven personalised learning systems can be beneficial. Additionally, the findings indicated that artificial intelligence should be integrated into the school curriculum for effective classroom instruction. This aligns with Holmes, Bialik, and Fadel's (2019) assertion that the integration of AI in education is transforming traditional pedagogical approaches, offering innovative solutions for addressing diverse learning needs and improving overall educational outcomes.

Thirdly, the findings suggest that blending indigenous and modern pedagogies will enhance students' learning through the integration of artificial intelligence. This is in line withUwadia's (2021) claim that AI has the potential to revolutionise teaching methods by providing adaptive learning platforms, intelligent tutoring, and data-driven decision-making. Finally, the study reveals that teaching in local languages using artificial intelligence will not enhance students' understanding in Junior Secondary schools.

5. Conclusion and Recommendations

The study concluded that the integration of artificial intelligence in educational management demands strategic government policy support for professional capacity building and sustainable investment in digital infrastructure to promote African indigenous pedagogies. The integration of artificial intelligence into storytelling encourages creativity and imagination among students, aligning with 21st-century learning. Integrating artificial intelligence in the 21st century will not only enhance pedagogies but will also help students develop collaborative skills needed in AI pedagogies, such as intelligent learning systems, data analytics for performance monitoring, and automated administrative processes, which significantly improve instructional delivery in African pedagogies. Additionally, AI has the potential to transform African pedagogies, enhance instructional strategies, and prepare students for a technology-driven world.

To ensure the benefits of integrating AI into African pedagogies for classroom instruction and to align with 21st-century learning, efforts must focus on investing in digital infrastructure and introducing AI into the curricula. However, addressing challenges such as inadequate infrastructure, a lack of AI awareness, and ethical considerations is necessary for the successful integration of AI into African pedagogies. The implications of these findings are important for building an inclusive and innovative education system in secondary schools in Kogi State. This study has contributed to knowledge by bridging technology, management, and culture, providing localized African pedagogies on AI in secondary schools in Kogi State, Nigeria. However, the limitation of this study is its focus on a single geographical zone in Nigeria.

The study recommends that the government, through the Ministry of Education, should develop a national framework that:

- Includes specific guidelines for incorporating indigenous pedagogies.

- Invests in stable internet connectivity, smart classrooms, and AI-powered learning management systems.
- Mandates maximum digital infrastructure standards for schools and establishes mandatory professional development on AI literacy for teachers and school administrators.

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CHAPTER SIX

Artificial Intelligence-Enhanced Work-Integrated Learning in Chemistry Education: Bridging Laboratory Theory and Professional Practice

Bamidele Emmanuel Tijani
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
Omolabake Temilade Ojo
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
Ayotomiwa Abel Akinde
Department of Science Education,
Faculty of Education, University of Lagos, Akoka, Yaba, Lagos, Nigeria
Godswill Ernest Irilochuwe
Department of Science Education,
Faculty of Education, University of Calabar, Cross River State, Nigeriass
Corresponding author: Bamidele Emmanuel Tijani (tijaniemmanuelb@gmail.com)

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Abstract: The integration of artificial intelligence (AI) into higher education is transforming the design and delivery of Work-Integrated Learning (WIL), especially in laboratory-based disciplines such as chemistry. This chapter examines how AI-enhanced WIL can connect theoretical chemistry knowledge with authentic professional experiences, fostering innovation, inclusivity, and skill development in the digital age. Drawing on constructivist and experiential learning theories, the chapter conceptualises AI as both a learning partner and a catalyst for professional competence. It investigates recent advancements in AI-supported feedback, adaptive mentoring, and virtual laboratory simulations to propose a framework for integrating AI-driven tools into chemistry WIL contexts. The chapter illustrates how AI-enabled platforms can facilitate reflective observation, provide real-time feedback, automate assessments, and ensure equitable access to laboratory experiences, all while aligning with emerging principles of authentic assessment and ethical AI use to maintain a human-centred and contextually relevant learning approach. By merging conceptual analysis with a practical implementation model, the chapter underscores the transformative potential of AI in enhancing student readiness, collaboration, and problem-solving within chemistry education. It concludes with recommendations for higher education institutions and industry partners to develop sustainable AI-mediated WIL systems that strengthen laboratory practice, improve employability, and promote inclusive participation in science education across diverse contexts.

Keywords: Artificial intelligence, chemistry education, experiential learning, laboratory innovation, work-integrated learning.

1. Introduction

The rapid advancement of artificial intelligence has begun to reshape higher education in ways that extend far beyond administrative efficiency or automated instruction. Recent developments indicate a shift towards intelligent learning environments that can complement and enhance human teaching, particularly in disciplines where complex problem solving, laboratory practice, and professional competence are central. Chemistry education has witnessed notable advancements in this area, with researchers reporting an increasing utilisation of digital and intelligent tools to support conceptual learning, assessment, and laboratory practice (Ali et al., 2023; Iyamuremye et al., 2024). Studies suggest that artificial intelligence can enhance key components of chemistry instruction, such as formative assessment, feedback quality, and the modelling of multistep problem-solving processes (Ade-Ibijola et al., 2025; Eitemüller et al., 2023). This emerging body of evidence implies that artificial intelligence possesses substantial potential to strengthen learning environments in laboratory-based disciplines where traditional teaching often encounters structural limitations.

A related development is the expanding role of Work-Integrated Learning (WIL) as an educational approach designed to connect theoretical knowledge with practical experience. WIL is recognised across higher education as an effective means of enhancing student employability, professional identity formation, and real-world competence (Curto-Reverte et al., 2025; Ferns et al., 2025). Despite its advantages, traditional models of WIL frequently encounter persistent challenges. These challenges include restricted placement opportunities, variable industry engagement, uneven supervision, and resource constraints that limit meaningful access for many students (Amarathunga, 2024; Cameron et al., 2019). Such challenges are particularly pronounced in chemistry education, where laboratory-based learning is contingent upon specialised infrastructure, safety considerations, and access to equipment. Consequently, students often experience disparities in the quantity and quality of hands-on laboratory practice that universities can provide.

Artificial intelligence has been identified as a potential means of addressing these constraints within laboratory-oriented disciplines. Research on virtual laboratories demonstrates that simulated experimentation can significantly enhance students' academic achievement, conceptual understanding, and confidence when compared with, or used alongside, traditional laboratory experiences (Asare et al., 2023; Bazie et al., 2024). These environments offer safe, scalable, and accessible alternatives for institutions that face infrastructural limitations. Complementary evidence from automated assessment research indicates that artificial intelligence can evaluate chemistry responses with increasing reliability, particularly for objective and structured items, while reducing marking workload and providing timely feedback (Ade-

Ibijola et al., 2025; Yamtinah et al., 2024). Parallel studies on explainable artificial intelligence feedback systems suggest that transparent recommendations improve student understanding and self-regulation, enabling learners to better comprehend the guidance they receive (Afzaal et al., 2024). These developments underscore the potential of artificial intelligence to support essential WIL functions such as supervision, assessment, feedback, and reflective learning.

There is further evidence that the integration of artificial intelligence aligns with contemporary pedagogical theories emphasising active engagement. Research on experiential learning indicates that generative artificial intelligence tools can support authentic tasks, enhance reflective processes, and facilitate deeper engagement in inquiry-based activities (Salinas-Navarro et al., 2024a, 2024b). Studies in related fields also demonstrate that artificial intelligence-supported simulations can foster reflective thinking and structured learning cycles consistent with experiential and constructivist principles (Kim, 2023; Lin et al., 2025). These insights suggest that artificial intelligence is not merely a technical enhancement but can significantly contribute to the theoretical foundations of WIL, provided it is employed within a pedagogically informed framework.

While research on artificial intelligence in chemistry education is expanding, there remains a notable gap at the intersection of artificial intelligence and Work-Integrated Learning. Existing studies have explored digital technologies in chemistry, the effectiveness of virtual laboratories, and automated assessment and feedback systems. However, there is limited research on how artificial intelligence can be systematically integrated into WIL to support authentic laboratory practice, improve feedback processes, enhance supervision quality, and ensure professional readiness (Ali et al., 2023; Bugaje & Madaki, 2025; Iyamuremye et al., 2024). The issue addressed in this chapter is the lack of a coherent framework that explains how artificial intelligence can strengthen Work-Integrated Learning in chemistry by improving access, enhancing feedback quality, supporting reflective practice, and promoting the human-centred principles necessary for meaningful experiential learning.

2. Conceptual and Theoretical Foundations

The conceptual and theoretical foundations of this chapter are based on established models of learning that advocate for active engagement, reflection, and authentic practice. Constructivist Learning Theory and Experiential Learning Theory serve as the basis for comprehending how learners cultivate deep knowledge through participation in meaningful tasks. These theories are particularly relevant to chemistry education, as laboratory work necessitates active interpretation, practical reasoning, and iterative refinement. Recent studies on artificial intelligence in science and chemistry education illustrate that intelligent tools can effectively align with these pedagogical traditions by reinforcing feedback loops, enhancing inquiry processes, and expanding access to authentic learning activities (Afzaal et al., 2024; Iyamuremye et al., 2024; Salinas-Navarro et al., 2024a). Consequently, this section outlines the two theoretical pillars that inform the analysis and positions artificial intelligence as a learning partner capable of supporting these established educational processes.

In practical terms, conceptualising artificial intelligence as a learning partner entails a structured and deliberate division of roles between technology and human educators. Artificial intelligence assumes responsibility for functions that are challenging to sustain at scale or in real time, including the provision of immediate formative feedback on laboratory tasks, the generation of personalised prompts during simulations, the monitoring of learner engagement through analytics, and the identification of misconceptions that require instructor intervention (Ade-Ibijola et al., 2025; Afzaal et al., 2024). Human educators, in contrast, retain responsibilities that necessitate professional judgement, relational sensitivity, and ethical reasoning — such as the design of learning experiences, the contextualisation of feedback, the moderation of assessment decisions, and the maintenance of supervisory relationships fundamental to Work-Integrated Learning (Ferns et al., 2025; Sharma & Sharma, 2025). Thus, the partnership is structured not as a replacement for human expertise but as an augmentation of educator capacity, enabling instructors to focus on higher-order mentoring and professional development while artificial intelligence manages the operational aspects of learner support. This understanding of the learning partnership ensures that the theoretical frameworks explored in this section are applied in a manner that upholds human-centred pedagogical values (Bugaje & Madaki, 2025; Opesemowo & Adekomaya, 2024).

2.1 Constructivist learning theory

Constructivist Learning Theory posits that knowledge is constructed when learners actively engage with concepts, observe outcomes, test assumptions, and negotiate meaning from their experiences. Learning is shaped by the individual contributions that learners bring to each task and by how they interpret feedback from their environment. This theoretical perspective is reflected in much of chemistry education, where understanding is developed through the interplay of conceptual explanations and laboratory investigations. Research in digital chemistry education confirms that students benefit from opportunities to work through problems in a structured yet exploratory manner. Eitemüller et al. (2023) demonstrated that digitalised multistep chemistry exercises, integrated with automated formative feedback, enable students to construct meaning by visualising errors, revisiting reasoning steps, and refining their approaches through guided practice. Such findings align with core constructivist principles, as they emphasise the value of scaffolded exploration.

Constructivism highlights the cognitive processes through which students derive meaning from laboratory work. In chemistry, learners do not merely observe chemical phenomena; they actively interpret results, reconcile unexpected outcomes with prior knowledge, and revise their conceptual understanding based on new evidence. This internal process of knowledge construction, which is rooted in the learner's interpretation of experience rather than in the cyclical structure of the experience itself, distinguishes constructivist learning from the experiential model discussed in the following section. Bazie et al. (2024) reported that virtual laboratory experiences enhanced students' academic achievement by allowing them to manipulate variables, observe outcomes, and revise their conceptual models in response to evidence. This process is grounded in constructivist meaning-making rather than procedural repetition. These findings illustrate how digitally mediated environments can support the interpretive and conceptual dimensions of laboratory learning that constructivism identifies as central to deep understanding.

Constructivist theory further emphasises the importance of feedback that aids in meaning construction. Afzaal et al. (2024) found that explainable artificial intelligence systems can provide transparent and interpretable feedback, helping students recognise misconceptions and regulate their learning. This aligns with the constructivist focus on learner interpretation of instructional cues. As chemistry learners engage in laboratory-based or simulation-based tasks, they rely on timely feedback to consolidate emerging ideas and establish conceptual coherence. Therefore, artificial intelligence tools can enhance constructivist learning cycles by providing consistent, detailed, and adaptive feedback in situations where human supervision may be limited.

2.2 Experiential learning theory

Experiential Learning Theory, particularly as articulated by Kolb, presents a cyclical model of learning consisting of four interrelated stages: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. This model closely mirrors the structure of chemistry laboratory work, where students design experiments, observe results, analyse data, articulate conclusions, and refine procedures. Research in chemistry and science education indicates that experiential learning fosters deeper conceptual understanding and enhances problem-solving skills. Furthermore, virtual and augmented environments in chemistry have been shown to engage students with the experiential cycle by providing simulated concrete experiences that can be repeated, adjusted, and reflected upon (Asare et al., 2023).

Research on artificial intelligence-mediated experiential learning provides additional insights into how this cycle can be enhanced. Salinas-Navarro et al. (2024b) found that generative artificial intelligence can support reflective observation by prompting students to explain their reasoning, revisit earlier decisions, and consider alternative approaches. Lin et al. (2025) demonstrated that generative artificial intelligence tools can foster reflective thinking in STEM contexts by providing structured prompts that assist students in articulating patterns and connecting experiences to broader principles. These studies highlight how the reflective and conceptual phases of Kolb's cycle can be strengthened through artificial intelligence-guided questioning, personalised feedback, and cognitive scaffolding.

Experiential Learning Theory also emphasises the importance of iterative experimentation. Chemistry education often necessitates that students repeat procedures, adjust parameters, and test new strategies. Virtual laboratories and simulation environments allow students to engage in these cycles without risk, resource limitations, or time constraints. Research by Bazie et al. (2024) provides empirical evidence that virtual laboratories support the experiential cycle by encouraging repeated experimentation and enabling learners to observe chemical processes in controlled, replicable conditions. When combined with artificial intelligence-based assessment or guidance systems, these environments can offer tailored suggestions that facilitate the transition from concrete experience to conceptual understanding. Such alignment strengthens the argument that artificial intelligence can enhance experiential learning structures in ways that support the development of practical and intellectual skills.

2.3 Positioning artificial intelligence as a learning partner

Artificial intelligence can be viewed as a learning partner when considered through the lenses of Constructivist Learning Theory and Experiential Learning Theory. Both theories emphasise active engagement, reflection, and iterative refinement, and emerging literature demonstrates that artificial intelligence systems can effectively support these processes. Constructivist Learning Theory posits that learners construct knowledge through interpretation, exploration, and feedback. Artificial intelligence systems align with these principles by providing continuous formative guidance, identifying misconceptions, and prompting learners to revisit earlier reasoning. Evidence from research on automated assessment indicates that artificial intelligence can deliver consistent and detailed feedback, enabling learners to interpret their performance and adjust their understanding, thereby reflecting the core tenets of constructivist meaning-making (Ade-Ibijola et al., 2025; Yamtinah et al., 2024).

Experiential Learning Theory further elucidates how artificial intelligence can operate within learning cycles. This theory outlines a sequence that includes concrete experience, reflective observation, abstract conceptualisation, and active experimentation. Artificial intelligence tools can facilitate each stage by providing simulated laboratory experiences, reflective prompts, and personalised suggestions that aid in developing conceptual understanding. Research indicates that explainable artificial intelligence systems can enhance reflective observation by assisting students in interpreting their data, understanding errors, and planning subsequent actions (Afzaal et al., 2024). Additionally, studies on generative artificial intelligence for experiential learning suggest that these tools can scaffold authentic tasks, promote engagement with real-world scenarios, and support transitions between reflection, conceptualisation, and experimentation (Salinas-Navarro et al., 2024a, 2024b). Such findings imply that artificial intelligence can play an integral role in the experiential cycle by offering timely input that facilitates repeated practice and informed decision-making.

Furthermore, artificial intelligence can enhance laboratory-based work-integrated learning (WIL) by addressing the supervision and access limitations that often hinder its implementation in chemistry education. Constructivism highlights the importance of guided exploration; however, instructors may not always be available to monitor students' decisions or provide immediate feedback in laboratory environments. AI tools can help bridge this gap by monitoring learner actions, offering context-sensitive guidance, and prompting real-time reflection. Additionally, AI-supported platforms expand the reach of WIL by allowing learners to engage in activities that replicate professional practice, even in the absence of physical placements or laboratory spaces. Studies confirm that such tools can foster the problem-solving, decision-making, and reflective skills that are essential for effective practice in laboratory-based disciplines, particularly when traditional supervision or infrastructure is limited (Ali et al., 2023; Bazie et al., 2024; Eitemüller et al., 2023).

Although constructivist and experiential learning theories provide a supportive foundation for the integration of AI, it is important to acknowledge that this alignment is not without tension. Some scholars caution that AI-mediated feedback may compromise the authenticity that is central to experiential learning, particularly if learners become reliant on algorithmically generated responses rather than engaging critically with the situated and contingent nature of real laboratory problems (Selwyn, 2019; Zawacki-Richter et al., 2019). From a constructivist perspective, concerns have also been raised that AI systems, regardless of their adaptability, cannot fully replicate the dialogic and relational dimensions of human mentoring that facilitate deeper meaning-making (Bayne, 2015). These critiques do not negate the potential of artificial intelligence to support learning; however, they do highlight the importance of designing AI-enhanced environments that preserve opportunities for genuine inquiry, human dialogue, and contextual professional judgement. The framework proposed in this chapter addresses these concerns by positioning artificial intelligence as a supplement to, rather than a substitute for, human-centred learning relationships.

Recognising artificial intelligence as a learning partner also clarifies how the theoretical foundations of this chapter inform the conceptual model developed later. Constructivist Learning Theory elucidates why learners benefit from personalised, interpretive feedback, while Experiential Learning Theory underscores the importance of iterative cycles of action, reflection, and refinement in laboratory practice. Positioning artificial intelligence as a learning partner within these traditions provides the conceptual basis for an AI-enhanced Work-Integrated Learning (WIL) model that is grounded in established principles of knowledge construction and professional competence development.

2.4 Concept of work-integrated learning and artificial intelligence in chemistry education

Work-Integrated Learning (WIL) is widely recognised as an educational approach that intentionally connects academic learning with authentic professional practice. In laboratory-based disciplines such as chemistry, WIL is particularly crucial as professional competence is cultivated through engagement with experimental procedures, instrumentation, safety protocols, and analytical reasoning. Chemistry WIL aims to immerse students in environments where theoretical knowledge is applied to real scientific tasks, thus fostering technical skills, professional judgement, and ethical awareness in line with workplace expectations (Curto-Reverte et al., 2025; Ferns et al., 2025). Through laboratory placements, industry-linked projects, and supervised practical experiences, students encounter the complexity and uncertainty inherent in scientific work, which enhances their readiness for professional roles.

The laboratory is central to WIL in chemistry education, serving as the primary space where abstract concepts are transformed into observable and measurable phenomena. Laboratory-based WIL enables learners to move beyond symbolic representations and engage directly with chemical reactions, data interpretation, and experimental decision-making. Research by Amarathunga (2024) and Ferns et al. (2025) indicates that such engagement enhances procedural fluency and deepens conceptual understanding, particularly when students are required to justify methodological choices and reflect on experimental outcomes. These experiences also contribute to employability by aligning academic learning with industry standards. However, the effectiveness of laboratory-based WIL depends on sustained access to well-structured and adequately supervised practical environments.

Despite its pedagogical value, traditional models of WIL in chemistry face persistent structural challenges. Limited laboratory space, high equipment costs, and strict safety regulations often restrict the frequency and duration of hands-on experimentation, especially in large undergraduate cohorts (Ali et al., 2023). Supervision challenges further compound these limitations. High student-to-instructor ratios can reduce opportunities for personalised feedback and reflective dialogue during laboratory activities, thereby weakening the learning potential of WIL experiences (Cameron et al., 2019). Consequently, some students complete chemistry programmes with uneven exposure to authentic laboratory practice.

Placement inequities also undermine the inclusive goals of WIL. Access to industry laboratories, research facilities, and specialised placements is uneven across institutions and regions. Curto-Reverte et al. (2025) reported that disparities in placement availability often disadvantage students from under-resourced contexts, resulting in unequal skill development and professional confidence. In chemistry education, where laboratory competence is central to professional identity, such inequities raise concerns about fairness and graduate preparedness. These challenges reveal a tension between the aspirational aims of WIL and the practical constraints of its traditional delivery.

In this context, artificial intelligence has emerged as a significant development in chemistry education, offering new ways to support learning and professional preparation. In both teaching and research settings, artificial intelligence assists with molecular modelling, reaction prediction, data analysis, and visualisation, addressing long-standing challenges related to abstraction and delayed feedback (Ali et al., 2023; Iyamuremye et al., 2024). The digital transitions in higher education, accelerated during periods of disruption, have further demonstrated institutional capacity to adopt intelligent learning systems that support flexible and technology-mediated laboratory learning (Opesemowo et al., 2022).

Recent trends indicate a growing utilisation of artificial intelligence-supported virtual laboratories, adaptive feedback systems, mentoring tools, and automated assessment platforms in chemistry education. Virtual laboratories facilitate repeated experimentation and safe exploration of chemical processes, thereby enhancing both conceptual understanding and procedural confidence (Asare et al., 2023; Bazie et al., 2024). Adaptive feedback and automated assessment systems offer timely responses to student work, promote self-regulation, and alleviate the burden of manual marking (Ade-Ibijola et al., 2025; Yamtinah et al., 2024). Furthermore, artificial intelligence-driven mentoring tools provide learners with guidance that emulates supervisory dialogue, particularly in situations where direct instructor support is limited (Afzaal et al., 2024).

While these advancements address challenges related to access, supervision, and scalability, their integration raises significant ethical and pedagogical considerations. Issues such as data privacy, transparency, academic integrity, and equitable access are central to responsible implementation. Research by Bugaje and Madaki (2025) and Opesemowo (2024) underscores the necessity for artificial intelligence in education to preserve learner agency, align with pedagogical intent, and uphold the human-centred values of professional preparation. It is crucial to ensure that artificial intelligence supports, rather than dictates, learning processes to maintain the educational integrity of WIL in chemistry (Opesemowo & Adekomaya, 2024). This integrated perspective positions artificial intelligence as a strategic enhancement of WIL that can strengthen laboratory practice while addressing longstanding structural limitations.

3. AI-Enhanced Work Integrated Learning: Conceptual Integration Framework

The AI-Enhanced Work-Integrated Learning (WIL) Conceptual Integration Framework (Figure 1) presented in this chapter synthesises insights from research in chemistry education, Work-Integrated Learning, and artificial intelligence. It illustrates how technology-mediated systems can enhance the connection between theoretical knowledge and professional laboratory practice. Grounded in constructivist and experiential learning theories, the framework positions artificial intelligence as a learning partner that fosters authentic engagement, reflection, and skill development within chemistry-based WIL contexts. It addresses documented challenges in traditional laboratory instruction, such as limited supervision, unequal access to placements, and constraints on practical exposure (Ali et al., 2023; Curto-Reverte et al., 2025; Ferns et al., 2025).

At the centre of the framework are the chemistry learners, whose development is shaped through iterative engagement with learning activities. Surrounding the learner are interconnected components mediated by artificial intelligence that support progression through Work-Integrated Learning activities. The first component, AI-supported feedback and reflective observation, draws on studies demonstrating the value of automated and adaptive feedback in promoting self-regulation and conceptual understanding. Research indicates that artificial intelligence systems can provide timely, consistent, and task-specific feedback, helping learners evaluate experimental outcomes and identify misconceptions. This feedback is essential for reflective learning in laboratory contexts (Ade-Ibijola et al., 2025; Afzaal et al., 2024; Yamtinah et al., 2024). This component aligns with experiential learning principles by strengthening the transition from concrete experience to reflective observation.

Linked to feedback is adaptive mentoring and personalised learning, which reflects evidence that artificial intelligence can guide learners through complex tasks when direct supervision is limited. Studies on explainable artificial intelligence and generative systems suggest that these tools can provide prompts, explanations, and recommendations that aid decision-making and scaffold learner progression (Afzaal et al., 2024; Salinas-Navarro et al., 2024a). In the context of chemistry WIL, adaptive mentoring supports constructivist learning by enabling learners to actively interpret guidance, test ideas, and refine their understanding during laboratory activities, rather than relying solely on prescriptive instruction.

The framework also incorporates virtual laboratory simulations and remote experimentation, supported by a growing body of research that highlights their role in expanding access to practical chemistry experiences. Virtual laboratories allow learners to conduct experiments, manipulate variables, and observe outcomes repeatedly in safe and controlled environments, addressing the infrastructural and safety constraints associated with physical laboratories (Asare et al., 2023; Bazie et al., 2024). These environments support experiential learning by enabling learners to engage in cycles of experimentation and revision, while also reducing inequities linked to limited laboratory space and placement availability (Curto-Reverte et al., 2025).

Another key element of the framework is the use of automated assessment and learning analytics for performance tracking. Artificial intelligence-based assessment systems have demonstrated their ability to evaluate conceptual understanding, problem-solving processes, and laboratory reports with consistency and efficiency (Ade-Ibijola et al., 2025; Eitemüller et al., 2023). The learning analytics generated by these systems allow educators to monitor learner progression, identify support needs, and assess the effectiveness of WIL activities at scale. This component reinforces authentic assessment practices while addressing the scalability challenges that are often encountered in chemistry education.

At the core of these components is a commitment to equitable access and inclusion, reflecting concerns raised in the literature about disparities in laboratory exposure, feedback quality, and placement opportunities. Artificial intelligence-mediated tools can promote inclusive participation by facilitating remote engagement, providing adaptive support, and offering flexible access to learning resources, particularly for students in under-resourced settings (Bugaje & Madaki, 2025; Opesemowo, 2024; Opesemowo & Adekomaya, 2024). Ethical considerations related to transparency, data privacy, and human oversight inform the design and implementation of the AI-enhanced WIL framework, guiding the selection, deployment, and evaluation of artificial intelligence tools within chemistry education contexts to ensure a human-centred approach to professional preparation (Bugaje & Madaki, 2025; Opesemowo, 2024).

Figure 1 illustrates the dynamic interaction among these components, demonstrating how artificial intelligence-mediated processes collectively support learner development within Work-Integrated Learning. The framework provides a theory-informed and evidence-based foundation for designing AI-enhanced WIL models that strengthen laboratory practice, improve feedback and assessment, and promote inclusive participation in chemistry education.

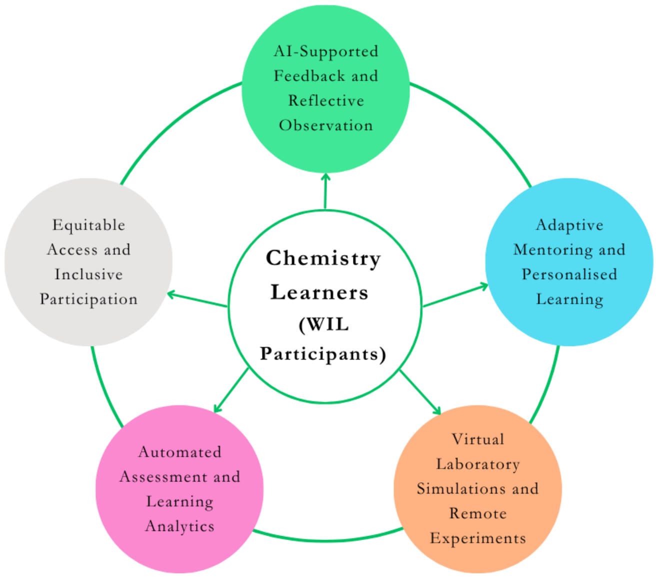

Figure 1. *AI-enhanced work-integrated learning framework for chemistry education*

The placement of the chemistry learner at the centre of Figure 1 is not merely structural but holds significant conceptual importance. Instead of interacting with each surrounding component in a fixed, linear sequence, the learner engages iteratively and concurrently across all four domains. This process involves receiving AI-generated feedback that encourages reflection, accessing adaptive mentoring when decision-making encounters obstacles, rehearsing procedures through virtual simulations, and having their progression monitored through learning analytics that identify areas necessitating instructor or teacher attention. This multi-directional connectivity ensures that each component reinforces the others: simulations generate the experiential data that feedback systems interpret; analytics reveal patterns that adaptive mentoring addresses; and the cumulative effect results in a coherent, learner-centred WIL environment. This design directly supports the central argument of the study that artificial intelligence, when positioned in relation to the learner rather than as a standalone tool, can address the structural limitations of traditional chemistry WIL while preserving the human-centred values of authentic professional preparation.

3.1 Sequencing and interaction of framework components in a typical WIL cycle

Although the components of the AI-enhanced WIL framework are described individually above, their pedagogical value lies in their dynamic interactions throughout a coherent learning sequence. The framework is not designed as a linear progression but as an iterative cycle, where each component activates and reinforces the others in response to the evolving needs of the learner. Understanding how these components interact in practice is essential for educators seeking to implement the framework within chemistry WIL.

In a typical AI-enhanced WIL sequence, students may begin with virtual laboratory simulations (component 3) to rehearse experimental procedures, manipulate variables, and build procedural confidence before engaging with physical or industry-linked laboratory settings. As they progress through simulated tasks, adaptive mentoring (component 2) provides scaffolded guidance, offering prompts that challenge assumptions, suggest alternative interpretations, and support informed decision-making in real time. Simultaneously, AI-supported feedback (component 1) analyses student responses to experimental outcomes, prompting reflection on observed data and facilitating the transition from concrete experience to conceptual understanding, in alignment with the reflective observation stage of Kolb's experiential learning cycle. Throughout this process, learning analytics (component 4) track performance patterns across all activities, identify students who may require targeted support, and generate evidence that enables educators to make timely and informed interventions. The interaction among these components is therefore neither linear nor autonomous, but a pedagogically structured cycle in which artificial intelligence augments and extends what human educators can offer, while human judgement provides the interpretive and ethical framework within which all AI tools operate.

3.2 Implementation and implications of AI-enhanced WIL framework

The implementation of an AI-enhanced Work-Integrated Learning framework in chemistry education necessitates deliberate institutional planning that aligns policy, curriculum, and digital infrastructure. At the policy level, higher education institutions must establish clear guidelines governing the ethical use of artificial intelligence, data protection, and academic integrity to ensure responsible adoption (Bugaje & Madaki, 2025; Opesemowo, 2024). These policies should explicitly recognise artificial intelligence as a pedagogical support rather than a substitute for human instruction. Curriculum redesign is equally critical, as chemistry programmes need to intentionally incorporate AI-mediated WIL activities within laboratory courses, industrial attachments, and capstone projects. Such integration ensures that artificial intelligence tools support defined learning outcomes related to professional competence, reflective practice, and problem-solving. Concurrently, investments in digital infrastructure, such as learning management systems, secure data platforms, and virtual laboratory technologies, are necessary to ensure scalable and reliable implementation (Ali et al., 2023; Iyamuremye et al., 2024).

Effective implementation also relies on strong collaboration between universities and industry partners. AI-enhanced WIL creates opportunities for shared supervision models, in which academic staff and industry professionals jointly support students through digitally mediated environments. For instance, virtual internships backed by artificial intelligence can allow students to engage with authentic industrial datasets, simulated laboratory workflows, or remote experimentation under the oversight of both academic and industry personnel (Ferns et al., 2025). Similarly, AI-based laboratory simulation platforms can be co-developed with industry to reflect current professional practices, equipment standards, and safety protocols, thereby enhancing the relevance of university training to workforce needs (Curto-Reverte et al., 2025). These collaborative models help bridge traditional gaps between theory and practice while expanding placement capacity beyond physical constraints.

Evidence of AI-enhanced WIL in practice is already emerging across higher education contexts. Institutions have begun integrating virtual simulations and AI-supported feedback into undergraduate programmes, enabling students to rehearse laboratory procedures and receive guided formative assessments beyond scheduled contact hours (Asare et al., 2023; Bazie et al., 2024). In some cases, artificial intelligence has been used to support virtual internships by monitoring task progression, offering prompts, and facilitating reflective reporting where direct supervision is limited (Afzaal et al., 2024). These emerging applications demonstrate that AI-enhanced WIL is not merely theoretical; it is a practical and scalable response to the structural constraints that have long limited the depth and equity of chemistry WIL experiences.

Ensuring a human-centred and ethical deployment remains a central consideration throughout the implementation process. Institutions must prioritise transparency regarding how artificial intelligence systems function, maintain human oversight in assessment and mentoring processes, and address equity issues in access to digital resources (Opesemowo & Adekomaya, 2024). When these conditions are met, the implications of the framework are substantial. Students benefit from enhanced professional competence, confidence, and employability derived from authentic, supported practice. Educators experience evolving roles as facilitators, mentors, and designers of learning experiences supported by artificial intelligence. For institutions and industry partners, AI-enhanced WIL strengthens collaboration, supports workforce relevance, and reinforces shared responsibility for ethical data use and professional preparation in chemistry education.

A further implementation consideration is how to assess AI-enhanced WIL activities and how they align with accreditation requirements for chemistry programmes. Professional bodies, such as the Royal Society of Chemistry (RSC) in the United Kingdom, the American Chemical Society (ACS), and equivalent national organisations, typically specify competency benchmarks that graduating chemists must demonstrate. These include laboratory skills, safety awareness, and professional conduct. Therefore, institutions adopting AI-enhanced WIL must ensure that AI-mediated experiences, such as virtual laboratory simulations and automated assessment tasks, are validated against these requirements, particularly when they are intended to fulfil mandated laboratory hours or practical competency standards. This may involve institutional review processes, formal engagement with accreditation bodies to clarify the standing of AI-mediated activities, and the development of equivalency frameworks that document how virtual and AI-supported experiences meet professional standards. Failing to address these accreditation dimensions risks a decline in institutional recognition of AI-enhanced WIL and may limit the transferability of students' credentials across professional and national contexts (Ferns et al., 2025).

3.3 Challenges and ethical considerations for implementation of AI-enhanced WIL

The implementation of AI-enhanced Work-Integrated Learning (WIL) in higher education presents significant pedagogical benefits; however, it is accompanied by structural and ethical challenges that require careful consideration. A primary concern relates to digital equity and infrastructural disparities across institutions and regions. Although artificial intelligence can enhance access to learning resources, virtual laboratories, and personalised support, its effectiveness is contingent upon the availability of reliable digital infrastructure. Research on technology integration in chemistry education indicates that limited access to laboratory facilities, digital tools, and technical support already constrains practical learning in numerous institutions (Ali et al., 2023; Mahbub et al., 2024). Nwakocha et al. (2025) emphasise that, while AI-driven systems possess the capacity to promote inclusive learning and employability, unequal access risks reinforcing existing educational inequalities. In AI-enhanced WIL contexts, students in under-resourced settings may, therefore, experience reduced exposure to simulations, adaptive mentoring, and analytics-driven feedback, thereby undermining the equity goals central to WIL (Curto-Reverte et al., 2025).

Closely linked to access is the challenge of safeguarding data privacy and academic integrity. AI-enhanced WIL environments depend on continuous data collection from student interactions with virtual laboratories, assessment platforms, and feedback systems. While such data facilitate adaptive learning and performance tracking, they also raise concerns regarding surveillance, data security, and potential misuse. Huang (2023) highlights that the widespread adoption of AI in education has intensified ethical risks related to student data privacy, particularly in systems that collect sensitive personal and academic information. Within chemistry education, automated assessment and AI-supported feedback systems have demonstrated efficiency and consistency (Ade-Ibijola et al., 2025; Yamtinah et al., 2024); however, their deployment must be accompanied by transparent governance structures. Bugaje and Madaki (2025) emphasise that ethical AI use in education necessitates clarity concerning data ownership, informed consent, and accountability to preserve trust and uphold academic integrity.

Another critical concern is the risk of over-automation, which may undermine the human-centred foundations of Work-Integrated Learning. WIL is inherently relational, relying on supervision, mentoring, and professional judgement to support learner development. While AI-driven mentoring and feedback tools can supplement instructional support, excessive reliance on automation may diminish opportunities for reflective dialogue and contextual guidance. Afzaal et al. (2024) demonstrate that explainable AI can support self-regulation; however, they also stress the importance of human interpretation in learning processes. Sharma and Sharma (2025) similarly caution that generative AI tools, if uncritically adopted, may displace meaningful educator involvement in WIL programmes. In chemistry education, where professional responsibility and ethical reasoning are cultivated through guided practice, the risk of over-automation extends beyond pedagogy into the domain of safety (Ferns et al., 2025).

Beyond the general ethical concerns surrounding AI in education, chemistry education presents discipline-specific ethical considerations that require explicit attention. A particularly significant issue pertains to the role of AI in safety training. Laboratory safety in chemistry relies not only on procedural knowledge but on embodied competence: the ability to identify hazards through sensory experience, respond appropriately under pressure, and cultivate a professional culture of caution and responsibility (Cameron et al., 2019). Although AI simulations can model safety protocols and present hazard scenarios in controlled virtual environments, they cannot fully replicate the physical, sensory, and affective dimensions of real laboratory risk management. Institutions must therefore ensure that AI-mediated safety training is deliberately supplemented with supervised hands-on experience, rather than being treated as a substitute.

Another chemistry-specific concern pertains to the use of AI-generated data in experimental contexts. Students who rely on AI-produced outputs, such as simulated spectra, predicted reaction yields, or algorithmically generated datasets, may develop an inaccurate understanding of experimental variability, measurement uncertainty, and the reproducibility challenges inherent in authentic laboratory science. Educators and curriculum designers must explicitly address this risk, ensuring that learners understand the limitations of AI-generated data and can critically evaluate its relationship to real experimental practice.

Together, these challenges underscore the need for a balanced and principled approach to implementing AI-enhanced WIL. Addressing infrastructural inequities, protecting data privacy, and avoiding over-automation are not peripheral concerns but core conditions for ethical and effective practice. By embedding artificial intelligence within robust pedagogical frameworks and maintaining human-centred supervision, higher education institutions can harness AI to strengthen, rather than compromise, the educational and professional aims of Work-Integrated Learning.

4. Conclusion and Recommendations

This chapter examines the integration of AI into WIL within chemistry education as a strategic response to ongoing challenges in laboratory-based instruction. Drawing on constructivist and experiential learning theories, the discussion establishes that AI can serve as a learning partner, enhancing access to authentic practice, supporting reflective learning, and strengthening the connection between theoretical knowledge and professional laboratory competence. Evidence from the literature indicates that AI-supported virtual laboratories, adaptive mentoring systems, automated assessments, and analytics-driven feedback can alleviate constraints related to limited infrastructure, uneven supervision, and inequitable placement opportunities. When thoughtfully implemented, these tools facilitate repeated experimentation, timely feedback, and personalised guidance, all of which are central to effective experiential learning and professional preparation in chemistry.

The chapter also proposes an AI-enhanced WIL conceptual framework that integrates feedback, simulation, mentoring, and assessment within a human-centred pedagogical structure. This framework illustrates how AI can reinforce experiential learning cycles while maintaining the supervisory and reflective dimensions essential to WIL. However, the analysis highlights that the educational value of AI is contingent upon ethical implementation, transparency, and sustained human oversight. Issues of data privacy, digital equity, and over-automation remain critical considerations, particularly in laboratory-based disciplines where professional judgement, safety awareness, and ethical reasoning are developed through guided practice. Therefore, the discussion positions AI as a transformative yet complementary tool, capable of enhancing laboratory learning and employability when aligned with sound pedagogical principles.

Several key recommendations emerge from this analysis. First, higher education institutions should develop clear policies regulating the ethical use of AI, focusing on data privacy, transparency, and academic integrity in WIL. Second, chemistry curricula should be intentionally redesigned to incorporate AI-supported simulations, feedback, and assessment activities that align with defined professional and laboratory learning outcomes. Third, universities should strengthen collaboration with industry partners to co-design AI-enhanced WIL experiences that reflect authentic workplace practices and shared supervision models. Fourth, targeted professional development should be provided for both educators and students to build the digital, pedagogical, and critical skills necessary for the effective and responsible use of AI in WIL settings. Lastly, sustained interdisciplinary research should be encouraged to evaluate the long-term pedagogical, ethical, and employability impacts of AI-enhanced WIL in chemistry education, with findings used to refine and adapt emerging frameworks as the technology continues to evolve.

4.1 Limitations of the study

It is crucial to recognise the limitations inherent in this conceptual analysis. The framework presented in this chapter has not undergone empirical validation; rather, it is based on a synthesis of existing literature and theoretical considerations, rather than primary data derived from chemistry WIL programmes. Consequently, the proposed model necessitates validation through pilot studies, case studies, and longitudinal research conducted across a range of institutional contexts and national environments. Furthermore, the analysis is specifically centred on chemistry education; while many of the principles discussed may hold relevance in other laboratory-based disciplines, caution should be exercised in generalising the framework beyond its intended scope. Another limitation pertains to the rapid pace of AI development: specific tools, platforms, and applications referenced in this chapter may evolve considerably in the near term, potentially altering the landscape of AI-enhanced WIL in ways that the present analysis cannot fully anticipate. The framework has been designed with this consideration in mind; its principles are intended to be adaptable rather than tool-specific, but ongoing review and revision will be necessary as the evidence base matures.

5. Declarations

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Use of Artificial Intelligence: During the preparation of this manuscript, the authors utilised AI-assisted writing tools, specifically Claude AI (Anthropic) and ChatGPT (OpenAI), solely for the purposes of language construction, sentence coherence, and editorial clarity. These tools were not employed to generate ideas, produce original arguments, conduct literature searches, or draw conclusions. All conceptual content, theoretical analysis, framework development, and scholarly interpretation are entirely the work of the authors. Following the use of these tools, the authors carefully reviewed and edited all AI-assisted passages to ensure that the resulting text accurately reflects their original meaning and intended scholarly contribution. The authors take full responsibility for the integrity, accuracy, and originality of the content of this publication.

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CHAPTER SEVEN

Bridging Artificial Intelligence, Equity, and Innovation in Early Childhood Teacher Education: Strategic Recommendations and Future Directions

Sifiso Everelly Ncube

Department of Childhood Education,

Faculty of Education, University of the Free State, Qwaqwa, South Africa

Corresponding author: Sifiso Everelly Ncube (2026964078@ufs4life.ac.za)

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Abstract: This chapter assesses how artificial intelligence (AI) is being integrated into Early Childhood Teacher Education (ECTE), focusing on equity, ethics, and innovation in relation to Work-Integrated Learning (WIL). It draws upon Bronfenbrenner's socio-ecological systems model, Wenger's concept of communities of practice, and critical equity and transformative pedagogies. The chapter conceptualises AI-mediated WIL as a relational ecosystem linking pre-service teachers, mentors, lecturers, and EdTech developers. A qualitative multiple case study methodology was employed to examine the experiences of urban, peri-urban, and rural-based pre-service teachers, mentors, and college lecturers in relation to the use of AI-based WIL. Data were collected through various methods, including semi-structured interviews, focus group discussions, and document analysis. Data collection and analysis involved the application of thematic and cross-case methodologies. Findings from the research indicate a tri-narrative approach whereby AI can provide increased levels of reflection, strengthen mentoring, and enhance opportunities for collaboration and innovation for ECTE students. However, differences in the availability of infrastructure, digital competencies, and ethical governance can limit access to equitable participation. Equitable access to AI-based WIL will require support mechanisms such as mentorship, participatory governance, and support from colleagues and institutions. As such, the RAIIF provides an evidence-based framework for the effective implementation of AI at micro, meso, and macro levels through ethical oversight, co-created innovation, and ongoing professional development. Finally, the chapter will provide recommendations for policymakers and practitioners to promote equitable, culturally responsive, and ethically governed AI-mediated WIL.

Keywords: Artificial intelligence, equity, innovation, early childhood teacher preparation, work-integrated learning.

1. Introduction

The utilisation of Artificial Intelligence (AI) is significantly impacting global education, particularly in the preparation of pre-service teachers and the learning experiences of students (Holmes et al., 2023). In the context of early childhood teacher education, AI has introduced new opportunities through adaptive assessments, simulation-based teaching practices, and predictive analytics regarding student performance. However, this transformation also presents substantial ethical, social, and pedagogical challenges. Researchers caution that, if left unchecked, AI may exacerbate structural inequities, particularly in low-resource settings (Knox, 2024). Therefore, it is both timely and critical to understand how to bridge the intersections of AI, equity, and innovation within teacher education.

Early Childhood Education (ECE) occupies a unique position in this discourse. ECE is distinctly relational, context-dependent, and value-based. Teacher education programmes, often integrated with Work-Integrated Learning (WIL), highlight the importance of authentic practical experiences and reflective supervision (Darling-Hammond & Hyler, 2023). Consequently, the implementation of AI in human-centred fields, such as ECE, necessitates a careful re-evaluation of ethics, pedagogy, and power dynamics (Schoop & Lam, 2024).

AI technologies, including digital mentorship dashboards, learner observation analytics, and intelligent tutoring systems, possess the potential to enhance learning by providing real-time feedback and customising professional development (Zawacki-Richter et al., 2023). However, countries in the Global South encounter disparities in infrastructure, digital preparedness, and policy alignment, which could reinforce historical inequities (Williamson & Piattoeva, 2023). This chapter perceives AI as both a transformative opportunity and an equity challenge within early childhood teacher education. It critically examines how teacher education institutions can progress from mere technological adoption to intentional innovation ecosystems that prioritise inclusivity, human dignity, and collective education.

Despite these widespread advancements, a significant relative gap remains in Zimbabwe, where empirical and policy-focused research on AI in early childhood teacher education is still limited (Hlongwane, Shava, Mangena, & Muzari, 2024). Challenges such as varying digital infrastructure, limited institutional capacity, the absence of robust national AI guidelines in education, and unequal access to devices and connectivity hinder the meaningful implementation of AI in WIL and teacher education programmes (Tarisayi & Manhibi, 2024). Furthermore, the lack of indigenous, culturally responsive AI tools and insufficient professional development for teachers underscores the urgent need for nation-specific frameworks that align AI integration with Zimbabwe's socio-economic realities and equity objectives (Bulathwela, Pérez-Ortiz, Holloway, Cukurova, & Shawe-Taylor, 2024).

This chapter reviews recent empirical and policy literature on AI in early childhood teacher preparation and WIL, with a focus on equity and inclusion. It scrutinises ethical and governance issues such as data privacy, technology-driven bias, and culturally responsive, developmentally appropriate practices (Berson, Berson, & Luo, 2025). Building on this review, the chapter proposes an operational framework that links AI, equity, and educational innovation, employing participatory, stakeholder-driven approaches. For the integration of AI in Early Childhood

Teacher Education (ECTE) to be effective, the chapter argues for a shift from a technocentric adoption model to an ecosystem approach, which should adopt a relational stance and adhere to ethical governance principles.

1.1 Problem statement

The integration of AI technologies within educational environments is rapidly increasing due to pilot initiatives and vendor-led implementations. Early childhood teacher education, particularly WIL deployments, faces a pressing need to harness AI's potential for apprenticeship and reflection without compromising learner safety, data confidentiality, or equitable access. Berson et al. (2025) noted that current barriers to the effective use of AI in teacher preparation include governance frameworks that inadequately address the learner-specific ethical implications of using AI. This issue is exacerbated by unequal infrastructure at placement sites and a lack of co-design among mentors, students, and lecturers, further limiting the successful use of AI. Additionally, long-term research evidence supporting both the developmental and equity-related effects of using AI remains limited. In Zimbabwe, many barriers to effectively utilising AI to support ECEs are compounded by ongoing urban-rural digital divides, unreliable internet connections, a lack of access to adequate numbers of devices, and the absence of national policies addressing AI in early childhood settings (Reina-Parrado, Roman-Gravan, & Hervas-Gomez, 2025). Low institutional readiness exists, as few colleges of education are prepared to effectively integrate AI into their programmes, resulting in many mentor teachers lacking essential digital pedagogy experience. Moreover, limited institutional awareness and understanding of AI among some lecturers constrains meaningful adoption and training (Holmes et al., 2022). Furthermore, the lack of robust enforcement of child data protection laws (Chen, 2024) heightens concerns about data protection, while parental distrust of AI, fueled by socio-economic vulnerabilities, further complicates the responsible adoption of AI in early childhood contexts.

1.1.1 Questions

This chapter was guided by the following questions:

- How do empirical and policy literature characterise the applications of AI in early childhood teacher education and WIL, particularly from an equity perspective?
- What are the key ethical, governance, and equity challenges associated with integrating AI into early childhood teacher education and WIL?
- What strategic and operational frameworks can effectively bridge AI, equity, and innovation in early childhood teacher education?

2. Theoretical Frameworks

The incorporation of AI into early childhood teacher education, particularly in WIL, requires a rigorous theoretical grounding that accounts for the multifaceted, relational, and socio-technical nature of these learning ecosystems. This chapter employs a triangulated theoretical framework that includes Socio-Ecological Systems Theory (Bronfenbrenner, 1979), Communities of Practice (CoP) Theory (Wenger, 1998), and Critical Equity and Transformative Pedagogy Frameworks (Ahmed, 2025). Together, these frameworks provide an integrated understanding of how AI can serve as a teaching/learning tool, a relational mediator, and a socio-ethical intervention.

2.1 Socio-ecological systems theory

Bronfenbrenner's Socio-Ecological Theory views human development through a series of nested layers of social systems, ranging from micro-systems (the immediate environment, i.e., the classroom) to meso-systems (interconnections between various institutions and people, e.g., family and institutions of higher learning), exo-systems (policies, technology, and governance structures that affect WIL experiences indirectly), macro-systems (national education policy, cultural values, and perceptions of AI in pedagogy), and the chronosystem (temporal aspects, including longitudinal adoption of AI, changing policy, and generational changes in digital literacy; Moloi, 2023).

The application of socio-ecological theory to the implementation of AI in education provides insight into how interconnected stakeholders across multiple levels can develop ethical, equitable, and innovative approaches to AI and pedagogy. As Darling-Hammond and Hyler (2023) argue, this also implies that an approach to AI governance will be required at a systems level, rather than as individual technological solutions.

2.2 Communities of practice (CoP) theory

Wenger's (1998) Communities of Practice (CoP) framework conceptualises learning as a form of social participation, wherein knowledge is collaboratively constructed through shared engagement, cooperative endeavour, and mutual accountability. In the context of early childhood teacher education, artificial intelligence (AI) can serve as a mediating technology that enhances the social learning processes inherent to Wenger's CoP model. For instance, emerging AI-enabled dashboards provide mentors and pre-service student teachers with real-time insights into classroom interactions, thereby facilitating learning through more informed and timely reflective practice. AI-generated analytics additionally promote the collective construction of knowledge by creating opportunities for dialogue among student teachers, mentors, and supervisors. Furthermore, AI tools can sustain engagement across placements by archiving reflective logs, lesson plans, and classroom observations, which collectively enable longitudinal learning. Positioning AI within CoPs highlights the relational and participatory dimensions of innovation, emphasising that technology must support rather than substitute the human interactions fundamental to work-integrated learning (WIL) (Jain, 2025; Ngcobo & Mpofu, 2024). CoP theory also underscores the value of distributed expertise, whereby lecturers, in-service mentors, and educational technology developers collaboratively engage in learning and co-design AI-mediated interventions, thereby cultivating an ecosystem of continuous professional growth.

2.3 Critical equity and transformative pedagogy

Transformative pedagogy emphasises the significance of dialogue, agency, and cultural responsiveness in facilitating change within educational settings. By fostering dialogue, students are afforded the opportunity to examine their roles in the dynamic ways that AI influences their engagement in practice, promotes equity, and shapes child development (Ahmed, 2025; Fleer, 2023). Transformative pedagogy recognises the crucial role of agency and voice in advocating for the inclusion of marginalised communities in both the design and policy-making processes surrounding AI systems. Moreover, transformative pedagogy advocates for cultural responsiveness to ensure that AI tools reflect the local language(s), pedagogical practices, and values of specific communities, thereby addressing potential cultural biases and homogenisation (Fleer, 2023). Furthermore, transformative pedagogy encourages institutions to engage critically with the ethical considerations surrounding AI, including data privacy, consent, and equitable algorithms. In the absence of such accountability, data-driven technologies are likely to exacerbate existing inequities (Crawford, 2021). For instance, adaptive AI-based assessment tools must consider learners' diverse socio-linguistic backgrounds to prevent disadvantages for certain groups and inaccuracies in representing teacher performance.

Consequently, it can be asserted that socio-ecological systems theory, CoP, and critical equity pedagogy provide a framework for analysing the process of implementing AI technology in education. According to socio-ecological systems theory, it is possible to account for the multi-level environmental model within which the technology will be implemented, thereby elucidating the interrelations among various systems, including class, community, and state (Bronfenbrenner, 1979). Concurrently, the central tenet of CoP theory is to focus on social learning during the process of Work Integrated Learning (WIL), wherein AI technology is employed to promote reflective thinking and learning (Wenger, 1998).

3. Review of Related Literature

The inclusion of Artificial Intelligence (AI) in both early childhood educator preparation programmes and work-integrated learning (WIL) will dramatically transform all aspects of educational settings, policies, and perceptions of educational equity. Empirical and policy literature agree that AI's transformative potential is both significant and deeply dependent on how issues of access, ethics, and inclusivity are addressed.

3.1 AI in early childhood teacher education and WIL: An equity-focused synthesis

The emergence of AI has become one of the most transformative forces within global education. The rapid development of research on AI's ability to provide personalised learning, support assessment, and automate educational processes is well documented in the work of Holmes et al. (2023) and Zawacki-Richter et al. (2023). Through Jain's work (2025), new technologies such as Natural Language Processing (NLP), predictive analytics, and intelligent tutoring systems have altered how teacher preparation is delivered, transforming the way teachers prepare for their roles. This allows for dynamic feedback loops between developmental milestones and technologies for learning, thereby enhancing metacognition and supporting teachers as learning orchestrators instead of content transmitters (Choi, 2025). AI tools, such as generative chatbots and intelligent lesson planners, are being used to assist pre-service teachers with lesson planning, classroom decision-making, and reflective practice during work-integrated learning (WIL) placements. However, despite the potential benefits, the literature highlights that AI innovation can obscure the long-standing inequities present within society (Barbieri and Nguyen, 2025). Fleer (2023) identifies issues related to access, representation, and agency as needing further examination; similarly, Crawford (2021) points out that AI systems frequently reproduce data biases from past iterations. Additionally, Moloi (2023) and Ngcobo and Mpofu (2024) highlight that infrastructure disparities, digital literacy, and policy gaps within the Global South limit equitable adoption of AI within teacher education. Therefore, it is imperative that AI integration into teacher education occurs intentionally and is equity-driven.

3.1.1 AI in early childhood teacher education

Early childhood teacher education aims to empower teachers with the knowledge and skills to facilitate children's development using play-based, inclusive, and culturally responsive teaching strategies (Darling-Hammond & Hyler, 2023). The emergence of AI in early childhood teacher education has brought both benefits and drawbacks. AI can support the development of pre-service student teachers' reflective practices by providing feedback from an AI system after they use AI-supported observation tools that analyse video recordings of classrooms to identify teacher-learner interactions (Knox, 2024), thereby improving their professional judgments.

On the contrary, AI-supported observation tools reduce complex human interactions to calculable elements, potentially diminishing the relational, emotional, and ethical aspects of ECE practice (Schoop & Lam, 2024). AI-supported tools that automate observation and assessment may lead to a diminished recognition of the importance of contextualised knowledge and lived experiences (Karataş & Yüce, 2024). This is especially relevant to the area of sociocultural variation in child-rearing practices, language use, and learning expectations that exist among families of young children (Fleer, 2023).

3.1.2 Work-integrated learning in the age of AI

Work-Integrated Learning (WIL) in the Age of AI in early childhood teacher education provides students with both theoretical knowledge and practical application through WIL, creating a pedagogical link between the two (Cooper et al., 2024). By emphasising experiential learning opportunities, reflection, and mentoring, WIL enables students to engage in real learning settings.

The use of AI is changing how student teachers experience WIL, including virtual or hybrid practicum experiences such as AI-driven simulations, digital portfolios, and adaptive learning dashboards (Ngcobo & Mpofu, 2024). With these technologies, students can participate in practice-based activities and receive pedagogically relevant feedback based on their decisions from real-world classroom examples (Jain, 2025).

However, the success of AI-enhanced WIL relies on institutional capability, ethical oversight, and technological fluency among mentors and student teachers (Moloi, 2023). Without sufficient training, AI can become a mechanistic substitute for human apprenticeship rather than an additional support system. This necessitates strategic innovation ecosystems and partnerships among colleges, early learning centres, technology developers, and policymakers to co-create equitable AI tools grounded in pedagogical theory and local context.

3.1.3 Equity and digital inclusion in AI-enabled teacher education

The commitment to equity is fundamental to both teacher education and ethical artificial intelligence (Varsik & Vosberg, 2024). However, digital divides continue to persist, with research indicating that disparities exist along socio-economic and geographic lines (Moloi, 2023). Access to reliable infrastructure, digital literacy, and culturally appropriate content remains uneven, particularly in low-resource settings (Moloi, 2023).

The design and governance of artificial intelligence can either exacerbate existing inequities or mitigate them. For instance, automated systems developed primarily using Western data may reinforce linguistic and cultural biases, thereby limiting their applicability in ECE settings in Africa (Knox, 2024). Moreover, equity encompasses issues of representation and agency concerning who develops artificial intelligence systems, provides the data utilised to train those systems, and the educational values they embody (Crawford, 2021).

Consequently, the integration of equitable artificial intelligence will necessitate not only technological inclusion but also epistemological inclusion, recognising diverse ways of knowing and teaching (Fleer, 2023). This necessitates a call to develop 'decolonial' artificial intelligence in education (Williamson & Piattoeva, 2023), which emphasises the importance of creating technology that affirms the localisation of technological tools, indigenous knowledge systems, languages, and frameworks for child development.

3.1.4 Ethical and governance considerations

AI in education raises several ethical issues related to data privacy, surveillance, transparency, and accountability. As AI systems assemble and process vast amounts of learners' data, concerns arise regarding informed consent, learner data protection, and the opacity of technology (Holmes et al., 2022). These issues are exacerbated in ECTE due to the vulnerabilities of learners and student teachers, who are subject to observation and assessment.

Frameworks for governance, such as UNESCO's recommendation on the ethics of AI (2023) and the European Commission's ethics guidelines for trustworthy AI (2024), emphasise values of beneficence, non-maleficence, justice, and autonomy (Schoop & Lam, 2024). However, these global frameworks need to be adapted to fit local educational realities. Research conducted by Ngcobo and Mpofu (2024) indicates that many teacher education colleges in Sub-Saharan Africa lack clear procedures for governance concerning AI, resulting in ad hoc and uneven implementation. For example, in Kenya, the integration of AI in education remains inconsistent, with institutions adopting technologies independently and often without clear policy direction or standardised guidelines.

An emerging consensus advocates for participatory AI governance, where mentors and student teachers have a voice in decision-making (Schoop & Lam, 2024). Such participatory strategies can alleviate ethical risks while fostering transparency, trust, and shared ownership of digital innovation. While no Zimbabwe-specific research was found, these international challenges are likely exacerbated in Zimbabwe due to infrastructural and policy constraints, highlighting the urgent need for context-sensitive frameworks and investment to ensure unbiased, ethical AI integration in early childhood education (Aliyu, 2025).

3.1.5 Innovation ecosystems in early childhood education

Innovation in early childhood education has a greater chance of success when it is viewed as an ecosystem—a dynamic set of interactions and relationships among different entities, such as people, institutions, and technologies (Bronfenbrenner, 1979; Wenger, 1998). In the context of AI in early childhood education, innovation ecosystems will comprise the relationships between institutions of higher education, early childhood centres, ed-tech companies, and government agencies working collaboratively as co-creative partners (Darling-Hammond & Hyler, 2023).

More recent studies have emphasised relational agency, or the ability of parties to combine their differing areas of expertise and interests into a cohesive unit aimed at common goals (Schoop & Lam, 2024). Innovation ecosystems involving AI will require all parties to be mutually engaged in learning processes, ensuring that technology developers have some understanding of pedagogical realities, and that teachers become aware of the affordances of AI, using them critically and reflectively (Jain, 2025).

Across the continent of Africa, several initiatives, such as the African Union's AI for Development in Africa Framework (African Union, 2024), advocate for regional coordination to promote ethically and inclusively developed technologies. Nonetheless, the gap between policy aspirations and the readiness of institutions to implement these policies remains substantial (Moloi, 2023). Closing this gap will entail not only building capacity but also necessitate forward-looking thinking to anticipate how the rapid evolution of AI may redefine professional learning, ethics, and identity in early childhood education.

The use of Artificial Intelligence (AI) in early childhood teacher education and work-integrated learning is a double-edged sword when it comes to equity in the education sector of Africa, particularly in Zimbabwe, as represented in empirical and policy literature. There are two sides to this issue; on the one hand, AI-enabled adaptive learning platforms and intelligent content delivery systems, as noted by Chisom, Unachukwu, and Osawaru (2024), can personalise learning, increase access to underserved areas, and provide students with immediate, relevant feedback. The ability to enhance teacher professional development and improve teachers' digital skills for the next generation of education systems are among the benefits that these new technologies can bring, as mentioned by Tarisayi and Manhibi (2024).

However, the same body of literature also highlights many challenges related to equity that remain unaddressed. Numerous barriers to equity still exist, such as a lack of physical infrastructure, insufficient preparedness on the part of educators, and growing gaps in technology access, as stated by Qayyum et al. (2025). Therefore, if these issues are not appropriately addressed through focused funding and policy mechanisms, they will only serve to widen the gaps between those who have the resources and capabilities to take advantage of these new technologies and those who do not.

Furthermore, ethical considerations surrounding AI have also emerged, including data privacy, cultural relevance, and algorithmic bias; thus, the implementation of policies and regulations that promote equity and social justice is required (Chisom et al., 2024). Additionally, it has been identified that collaborative and long-term investment from all stakeholders is necessary to ensure that AI becomes a transformative tool for education rather than an exclusionary device.

4. Methodology

The qualitative, multi-case study design is appropriate for the chapter's objective of gaining an understanding of how AI, equity, and innovation are integrated into early childhood teacher education. It provides contextually rich information, captures participant perspectives, and offers strategic recommendations for policy and practice.

4.1 Research paradigm

This chapter employs a constructivist-interpretivist paradigm as the conceptual foundation for this research project. It is based on the premise that all knowledge is co-created through the interaction between the author and participants within social and cultural contexts (Creswell & Poth, 2023). Furthermore, the adoption of AI in early childhood teacher education has a relational component that is significantly influenced by the values, practices, and expectations of various stakeholders, including pre-service student teachers, mentors, college lecturers, and technology providers. Utilising an interpretivist paradigm allows for an exploration of ethical, equitable, and innovative dynamics (Denzin & Lincoln, 2023) while enabling a more detailed analysis of the ethical implications, power imbalances, and structural inequalities associated with the adoption of AI (Mnguni, 2024). The integration of these two paradigms in this chapter will provide the researcher with a robust empirical foundation and a normative perspective on the necessity of considering justice and inclusion when incorporating AI in early childhood teacher education.

4.2 Research approach

A qualitative research approach was employed to explore how stakeholders in early childhood teacher education construct their understanding of AI integration across different socio-cultural and infrastructural environments. This was achieved through methods such as document analysis, focus groups, and semi-structured interviews, which examined the lived experiences and ethical considerations of pre-service students, mentors, and lecturers. These methods provide insights into complex issues that cannot be identified through quantitative data (Mohammed, 2023). Additionally, through collaborative and ongoing dialogue, qualitative research offers a rich source of contextualised information on how issues related to equity, innovation, and relational pedagogy are developing in Zimbabwe's emerging AI environment (Mnguni, 2024).

4.3 Research design

The use of a multiple-case study design was based on several reasons. AI adoption in work-integrated learning (WIL) is characterised by various interrelated factors, including the technological infrastructure available, policies at the institutional level, mentorship practices, and the cultural context in which they are situated. These factors are most effectively explored using in-depth case-based research approaches (Mnguni, 2024). Examining numerous institutions and learning contexts allows for cross-case contrast, revealing patterns, deviations, and contextual nuances in AI integration, equity outcomes, and innovation practices. Case studies facilitate the development of practical and conceptual frameworks, linking socio-ecological theories, CoPs, and critical equity theories to real-world applications in teacher education (Creswell & Poth, 2023). The chapter focuses on one purposefully selected teacher education college, one highly resourced urban primary school, one fairly resourced peri-urban primary school in Bulawayo, and one poorly resourced rural primary school in Matabeleland North, Zimbabwe. This selection enables the exploration of both resource-rich and resource-constrained environments, highlighting equity and access challenges across different settings.

4.4 Participants and sampling

A purposeful sample was drawn to achieve diversity among participants' roles, institutions, and settings (Mnguni, 2024). The sample included nine student teachers on attachment as part of an AI-based WIL placement, representing different socio-economic backgrounds; six mentors who supervise student teachers in Early Childhood Development (ECD 'A' and 'B') classrooms; and four college lecturers who equip student teachers with the relevant knowledge, skills, and strategies to integrate technology.

Participant selection was based on achieving diversity in relation to geographical context (urban, peri-urban, and rural) and technological access (high and low infrastructure environments), as well as professional experience (mentors with varying experience in using AI). This sampling method ensured a deeper understanding of the multi-tiered dynamics influencing AI adoption, equity, and innovation.

4.5 Data collection methods

To establish reliability and legitimacy, the chapter employed a triangulated method for data collection. Semi-structured interviews were conducted with mentors and college lecturers to explore their perceptions on AI adoption, ethical considerations regarding AI, mentorship, and innovation (the interviews lasted 30-45 minutes, and all were fully transcribed). Three focus groups were held with pre-service student teachers to examine commonalities in their shared experiences, the challenges they encountered, and how they collaborated in the AI-mediated WIL setting. Document analyses were conducted on institutional AI policy documents to understand governance structures, working protocols, and equity-focused strategies. By employing a combination of qualitative methods, the author was able to enhance their understanding of this phenomenon and cross-validate the findings from each of the different methodologies used.

4.6 Data analysis

Data in this chapter will be presented and analysed in alignment with the primary guiding questions. This approach ensures coherence between the chapter objectives, data generation, and analytical procedures (Creswell & Poth, 2023). The data will be systematically organised according to each research question, enabling a focused interpretation of participants' perspectives. The analysis will incorporate the identification of themes, supported by relevant verbatim quotations, to enhance credibility and depth (Mnguni, 2024). Consequently, this method facilitates a structured and rigorous examination of the data while maintaining fidelity to the research aims.

4.7 Ethical considerations

Ethical integrity was vital to the chapter, particularly given the involvement of pre-service student teachers, mentors, and college lecturers (ECD) in WIL environments. The author applied for ethical clearance from the Provincial Education Director and from the principal of the participating teacher education college in Bulawayo Province. Furthermore, written consent was obtained from all participants who took part in semi-structured interviews and focus group discussions. Data were anonymised, and identifying information was removed. Pseudonyms were used in all reporting. Digital data were securely stored in password-protected systems, while hardcopy data were kept in lockable cabinets. The author engaged in reflexive practices to minimise bias and ensured a culturally sensitive interpretation of the findings.

4.8 Trustworthiness

To ensure that the credibility of this study is sufficiently high for it to be deemed transferable, dependable, and confirmable, the author employed a variety of strategies (Denzin and Lincoln, 2023; Creswell and Poth, 2023). The utilisation of multiple data collection methods and sources, all yielding similar results, contributed to the credibility of this research. Participants were also given the opportunity to review the initial findings, enabling them to validate the accuracy of the preliminary results and their relevance to their experiences. This study additionally includes detailed descriptions of the research context and the procedures followed, thereby enhancing its transferability. Furthermore, the author documented the decision-making process involved in developing the coding schemes and themes, as well as in interpreting the data, to provide insight into the transparent methodology that underpinned the development of the findings. The coding frameworks and thematic interpretations were also independently reviewed by other scholars, minimising author bias, which aligns with the peer debriefing strategy.

5. Presentation of Results

5.1 Empirical and policy literature of the applications of AI in early childhood teacher education and WIL

The views of lecturers (A, B, and mentor B) were similar. Lecturer A said that *"AI has the potential to enhance both ECD teacher preparation and work integrated learning (WIL), but barriers such as unequal access, cultural misfit and a lack of adequate infrastructure could limit its equitable use"* and lecturer B stated that "*unless implemented carefully, AI will have the potential to create even greater inequalities than exist at present between students undertaking the same qualification and the children they teach"*. Mentor B from an urban school stated that *"AI can be an opportunity to further develop student teacher learning opportunities; however, the disparity in terms of infrastructure, means that many placement locations do not provide an opportunity for meaningful use of AI."* Furthermore, she states that "*the disparity in this regard creates inequitable WIL experiences and inequitable preparation for early childhood teaching."* Student teacher 1 (from a focus group discussion across different contexts) acknowledged that AI had the potential to improve their learning but also stated that *"access and experience was largely determined by the quality of the infrastructure available within the placement schools that they attended."* She further explained that *"disparities in the access to technology in their schools' created disparities in the preparedness, confidence and assessment performance of their peers during teaching practice."* The analysis of institutional documentation indicated a recognition of the importance of developing teacher capacity; however, no concrete AI competencies were included in the pre-service curriculum for ECD. Furthermore, while there was acknowledgment of equity in the context of policy rhetoric (i.e. the urban/rural divide), the operationalisation of this concept in curricula was found to be weak. Finally, it was noted that there is currently no inclusion of AI-enabled practicum models in the existing WIL guidance. Overall, a closer examination of the findings from all data sources reveals that AI is perceived as having the potential to enhance early childhood teacher education and WIL. However, similar to other studies (Qayyum et al., 2025 & Zhou, 2025), it appears that the benefits of AI are being unequally realised and are constrained by issues related to infrastructure, curriculum, and contextual factors.

5.2 Key ethical, governance, and equity challenges associated with integrating AI into early childhood teacher education and WIL

The application of AI in ECTE and WIL has led to numerous ethical and governance issues. For instance, one of the most critical governance problems identified from the data analysis process is the governance gap associated with AI technology. This problem arises due to inadequate policy formulation and a lack of ethical guidelines regarding the appropriate use of AI technology in education, particularly in areas where vulnerable groups, such as children, participate in WIL. As stated by Student Teacher 2, *"Without explicit AI policies, ethical guidelines, and data-protection frameworks, we cannot be certain of how to responsibly implement AI tools with young children in our WIL settings."* From document analysis, it came out that there is no clear policy on AI integration in teacher education programs. Ngcobo & Mpofu, (2024) argue that lack of such clear definitions makes it easy for learning organisations to adopt AI technologies that might infringe on their clients' privacy or create room for bias (Crawford, 2021).

Moreover, another critical barrier to implementing AI in ECTE and WIL is access to adequate technology. Educational institutions from urban, peri-urban, and rural locations differ greatly in their physical setup, hence unequal access for learners to AI in their learning process. The digital divide is also a serious challenge since some schools lack the infrastructure and capacity to implement AI, as pointed out by Tarisayi and Manhibi (2024). The technological gap creates a problem where students from well-endowed institutions are better placed to utilise AI tools compared to those in poorly endowed locations.

Lastly, cultural and pedagogical issues emerged as other critical challenges when considering the effective implementation of AI in ECTE and WIL. Notably, the lack of context-specific AI tools that consider Zimbabwe's indigenous language and culture was a significant problem. Peri-Urban Mentor A stated, *"Poor capacity building for lecturers, mentors, and student teachers results in inconsistent or ad-hoc use of AI and raises serious ethical questions surrounding learner data, bias, and reliance on AI"* (Fleer, 2023). The lack of culturally sensitive AI resources could also make it hard for student teachers to use AI in their lessons. This is especially true for early childhood educators who have to meet specific pedagogical requirements to accommodate children's developmental needs. It is essential to develop AI tools that work effectively but also adhere to cultural and pedagogical values (Barbieri & Nguyen, 2025).

In conclusion, while AI has the capability of revolutionising teacher education at early childhood stages, it must be adopted responsibly to address the above ethical, governance, and equity issues. Without adequate frameworks, the adoption of AI could end up exacerbating inequities, especially in peripheral areas. According to the statistics provided above, the adoption of AI technology should go beyond technology but also involve ethical governance and cultural sensitivity, among others.

5.3 Strategic and operational frameworks to bridge AI, equity, and innovation in early childhood teacher education

The data reveal an evident void in coherent and contextualised AI frameworks used in Zimbabwean early childhood teacher education. This has resulted in an unevenly distributed, fragmented, and ethically risky use of AI. As a result of this lack of coherent and contextualised AI frameworks, lecturers and student teachers have called for both national and institutional policies that are explicit and contextualised to the Zimbabwean linguistic, cultural, and infrastructural realities. Lecturer D *emphasised, "we need comprehensive and contextually grounded frameworks to direct the ethical and equitable integration of AI in early childhood education and work-integrated learning."* Therefore, Lecturer D argued that there needs to be national and institutional policies that clearly articulate how to utilise AI in ways that are consistent with Zimbabwean cultural, linguistic, and infrastructural realities while providing equitable resource allocation. This is consistent with Socio-Ecological Systems Theory, which asserts that educational innovation is formed by the continuous interaction among individual, institutional, and societal factors (Ozturk, 2025).

Mentors at varying school locations reiterated their desire for a structured, equitable, and ethically sound framework to direct the incorporation of AI into ECD teaching practice. Mentor A at a peri-urban school stated that "we need specific guidelines on what tools are suitable, what the pedagogical uses of the tools are, and how to safeguard children using the tools, along with methods to localise AI content so it reflects Zimbabwean language and culture." Mentor C, at a rural school, emphasised that *"the most important step is to prioritise foundational accessibility like having enough power, devices, and offline-capable tools to enable meaningful AI utilisation."* This is consistent with Vesna et al. (2025) and Cabral & Palavras (2025), who noted that until there are operationalised equity commitments such as a minimum digital standard, mobile AI toolkits, or offline solutions, low-resource and rural schools will be systemically disadvantaged, similar to global concerns regarding the digital divide in AI-based education.

Student teachers similarly emphasised the need for a comprehensive and equitable AI integration framework that would provide them with clear pedagogical direction, practical skills development, and robust ethical protections. Student Teacher 3 at a peri-urban location expressed, *"there should be a structured, hands-on training programme that connects coursework with practical AI projects to build confidence and reduce uncertainty when conducting teaching practice."* Community of Practice (CoP) Theory is consistent with student teachers' desires for structured, hands-on training and well-prepared mentors, which are necessary for building confidence and reducing uncertainty, because a fragmented or inconsistent capacity-building process can lead to variable levels of support and inhibit the establishment of a community of expertise (Fleer, 2023). Student teachers' concern for fairness was prominent, with requests for a minimum amount of AI experience to occur in college labs, mobile digital kits, or offline-capable tools to allow for equitable assessment regardless of where students are placed for field experiences.

The policy review has revealed several critical knowledge gaps regarding the integration of Artificial Intelligence (AI) into Early Childhood Teacher Education (ECTE), particularly in Work-Integrated Learning (WIL). While many policies reference equity, rural inclusion, and digital access, operational strategies, minimum digital requirements, and provisions for low-tech environments are very rarely provided. This limits the alignment of these policies with the reality of educational systems. As indicated by Ahmed (2025) and Henriksen et al. (2025), the perspectives of Critical Equity and Transformative Pedagogy emphasise that without sufficient standards and ethical frameworks, digital divides will widen, inclusion will be undermined, and child-centred practices will be compromised. Furthermore, weak governance, limited capacity building, and a lack of adequate safeguards have exacerbated the fragmented nature of AI implementation in ECTE. Therefore, there is an urgent need for strategic, operational, and contextual AI frameworks.

6. Discussion of Findings

The primary objective of this chapter was to assess how both empirical and policy literatures have conceptualised the use of AI in ECTE and WIL) concerning issues of equity. From a socio-ecological perspective, the findings clearly demonstrate that disparities in the integration of AI within ECTE and WIL are multi-layered, occurring across micro, meso, and macro systems. At the micro level, inequalities manifest in classrooms where student teachers' access to AI-enabled tools, digital literacy, and opportunities for reflective practice vary significantly. The evidence indicating uneven access to devices, unreliable internet connectivity, and limited pedagogical preparedness highlights the need for interventions that directly support individual competencies and classroom practices (Ozturk, 2025; Qian et al., 2025). At the meso level, institutional disparities are evident in the uneven availability of infrastructure, professional development opportunities, and the absence of coherent institutional strategies for AI integration. The lack of alignment between policy intentions and institutional practices further exacerbates inequities. At the macro level, fragmented governance frameworks, policy gaps, and inconsistent national strategies constrain equitable AI adoption. These interconnected challenges justify the need for the RAIIF to adopt a multi-level structure that simultaneously addresses individual capacity building, institutional readiness, and policy coherence. The findings therefore support a framework that is layered, context-responsive, and capable of intervening across all levels of the educational ecosystem (Zhou, 2025).

From the perspective of Communities of Practice (CoP), the findings reveal a significant gap in collaborative and sustained professional learning environments necessary for effective AI integration. The variability in AI use and the reported lack of structured support systems indicate that many educators operate in isolation, without access to shared knowledge, mentorship, or collective problem-solving mechanisms. This absence of collaborative spaces limits innovation, particularly in resource-constrained contexts where peer learning and knowledge exchange are critical (Aliyu, 2025). The evidence highlighting the potential of communities of practice to provide mentorship, shared learning experiences, and contextually relevant solutions underscores the importance of embedding relational learning ecosystems within the RAIIF. Berson et al. (2025) and Ding (2025) suggest that such ecosystems would facilitate continuous professional development, enable the co-construction of knowledge, and support the adaptation of AI tools to local realities. Consequently, the framework must prioritise the establishment and sustenance of collaborative networks that bridge the gap between theory and practice, thereby enhancing both innovation and equity in AI integration.

Through a critical equity perspective, the findings underscore the risk that AI, if uncritically adopted, may reproduce or even exacerbate existing structural inequalities. Issues of cultural irrelevance, algorithmic bias, and unequal access to digital resources highlight the importance of foregrounding equity and inclusion in any framework for AI integration (Cabral & Palavras, 2025). The evidence suggests that current implementations often fail to account for diverse socio-cultural contexts, thereby marginalising already disadvantaged groups. Furthermore, Ahmed (2025) and Henriksen et al. (2025) argue that the persistence of policy rhetoric without concrete operationalisation points to a lack of accountability in ensuring equitable outcomes. These insights justify the inclusion of an explicit equity and inclusion lens within the Responsible AI Integration Framework (RAIIF), grounded in principles of social justice and transformative pedagogy. Such a lens necessitates the development of culturally responsive AI tools, the prioritisation of low-resource and offline-compatible technologies, and the implementation of ethical safeguards to protect vulnerable learners. It also requires mechanisms to translate policy commitments into actionable strategies that directly address inequities in access, participation, and outcomes (Aliyu, 2025; Zhou, 2025).

Taken together, the integration of these three perspectives provides a coherent and evidence-based justification for the RAIIF. The socio-ecological lens necessitates a multi-level and systemic approach; the CoP lens emphasises the importance of collaborative and relational learning structures; and the critical equity lens ensures that all interventions are guided by principles of inclusion, justice, and contextual relevance (Aliyu, 2025; Ozturk, 2025). The convergence of these findings highlights that effective AI integration in ECTE and WIL cannot be achieved through isolated or technocentric approaches but rather requires a comprehensive framework that is simultaneously structural, relational, and transformative (Wenger, 1998; Cabral & Palavras, 2025).

7. Conceptual Framework

The "Relational AI-Education Innovation Framework" (RAIIF) proposed in this chapter provides a guiding structure for integrating AI into early childhood teacher education. The RAIIF is a synthesis of the chapter's empirical and theoretical data, with an emphasis on equity-centred relational dynamics and multiple levels of focus.

7.1 Core components of RAIIF: Relational learning ecosystems

The WIL experience incorporates an AI-based mediation system to support interaction among a multitude of actors, including pre-service teachers, mentors, learners, lecturers, and other stakeholders (Darling-Hammond & Hyler, 2023). The WIL experience is framed using Socio-Ecological Theory and Community of Practice (CoP) models, which demonstrate that this is a collaborative and problem-solving process in a mentor-led environment where both professional development and contextualised learning of educators occur collaboratively.

7.2 Equity and inclusion lenses

Adopting AI in education is approached from a critical equity perspective, prioritising access for marginalised learners and the development of culturally responsive tools. Implementation approaches encompass multiple languages, infrastructure support, and mentorship structures, collectively aimed at removing educational discrepancies and creating equitable learning opportunities (Aliyu, 2025).

7.2 Ethical governance

Governance of AI in education includes strict policy compliance, stakeholder involvement in decision-making, data privacy safeguards, and technology-driven accountability, ensuring responsible enactment (Ngcobo & Mpofu, 2024). Such governance mechanisms operate across both institutional (mesosystem) and community (macrosystem) levels, facilitating harmonised oversight and alignment with broader ethical and regulatory standards.

7.3 Innovation and continuous adaptation

This method provides an iterative process of co-creative development and reflective practice with AI, allowing it to evolve to meet changing pedagogical and contextual needs. The method encourages experimentation, continuous feedback processes, and the development of a mechanism for adapting to challenges, ensuring that AI can be appropriately integrated into educational environments that are responsive and effective.

7.4 Operationalising RAIIF

The framework views AI integration in WIL across three levels. At the micro-level, it emphasises AI-mediated mentoring, reflective analytics, and adaptive lesson simulations; at the meso-level, it focuses on collaboration between institutions, curriculum development, and the formation of communities of practice; and at the macro-level, it addresses policy orientation, equity-oriented governance, and sustainable AI adoption techniques. The chronosystem dimension ensures ongoing monitoring and modification over time, including stakeholder responses and technological advancements. By integrating technology, pedagogy, equity, and ethics, the framework offers a practical and theoretically grounded approach for the implementation of AI in WIL programmes.

8. Conclusions and Recommendations

Taken together, these integrative perceptions depict AI as a relational and ethical ecosystem rather than a discrete technological solution. Effective integration relies on fostering insightful teachers, equitable access, collective mentorship networks, and governance systems that resonate with local contexts. These interdependencies create the conceptual foundation for a strategic framework of AI in ECD teacher education—one that recognises that technological innovation must be accountable for the human and cultural dimensions of learning.

8.1 Implications

The findings of this study have a variety of multi-layered implications for policy, practice, pedagogy, and research, particularly in relation to the intersections of AI, equity, and innovation in early childhood teacher education. These implications pertain to the socio-ecological dynamics, ethical governance, and relational learning ecosystems identified in this study.

8.1.1 Policy implications

AI must be integrated into classrooms with a focus on fairness for all, emphasising access, the use of tools that are both culturally and linguistically appropriate, and a strong technology infrastructure (Fleer, 2023). Policymakers at both national and local levels have the responsibility to create frameworks governing the ethics of using AI, specifically regarding the protection of student and teacher data privacy, establishing accountability, and obtaining informed consent (Ngcobo & Mpofu, 2024). Participatory forms of governance should involve preservice teachers, their mentors, and their communities to provide a greater level of transparency and representational voice. The sustainability of funding and investment will be critical to supporting the development of digital infrastructure, mentorship, and continuous professional development for teachers to achieve equitable long-term AI implementation (Fleer, 2023).

8.1.2 Pedagogical implications

Effective use of AI in teacher training requires mentorship-coached communities of practice (CoPs), wherein mentors possess expertise in using AI-based methods, reflect on their practices, and provide ethical supervisory support for students. The technology-based instruction delivered through AI must be culturally and contextually relevant to each student's environment, including their language, culture, and pedagogy; this is particularly important given the variety of educational settings (e.g. urban schools, rural schools, schools serving diverse populations, etc.) (Holmes et al., 2022). Furthermore, pre-service teachers should engage in structured cycles of reflection and utilise AI analysis to develop critical thinking, problem-solving, and professionally responsible judgments when making decisions regarding students' needs and instruction.

8.1.3 Institutional and partnership implications

Developing collaborative innovation ecologies necessitates the co-design of AI interventions by teacher education colleges, early learning centres, and EdTech developers, ensuring alignment with pedagogical goals, equity imperatives, and local contextual needs (Darling-Hammond & Hyler, 2023). Colleges must facilitate ongoing professional learning through sustained training in AI literacy and ethics, thereby empowering educators to engage responsibly with rapidly evolving technologies. Moreover, the active involvement of the community—encompassing the participation of families and local stakeholders in the co-design process—is vital for fostering transparency, confidence, and cultural relevance in AI-mediated educational practices.

8.1.4 Chapter implications

Forthcoming chapters on AI in education must prioritise longitudinal studies to evaluate the long-term effects of AI integration on teacher preparation, student outcomes, and systemic equity. Cross-cultural comparative studies are essential to identify best practices for culturally responsive AI adoption across varied educational and technological contexts (Ngcobo & Mpofu, 2024). Moreover, academic attention should emphasise technology-driven transparency, ethical oversight, and participatory governance models to alleviate bias and ensure the responsible application of AI interventions in early childhood education.

8.2 Strategic recommendations

This chapter highlights AI's ability to assist in transforming early childhood teacher education but emphasises that this will depend on the quality of equitable access, ethical governance, and relational practices. The findings indicate that AI has the potential to support mentoring, reflection, and professional development as a complement to human scaffolding. Realising AI's potential for the transformation of early childhood teacher education requires policy approaches to address issues such as equity in access to technology, digital literacy among teachers, the contextual relevance of AI applications, protecting data privacy, ensuring that AI is treated fairly, and promoting participatory, community-driven innovations.

8.2.1 For policymakers

National AI in education techniques should prioritise equity, ethical governance, and robust infrastructure support to foster inclusive and responsible technology integration (Darling-Hammond & Hyler, 2023). Policies must be formulated through participatory processes that encompass teachers, students, and community delegates, ensuring transparency and contextual relevance. Additionally, accountability frameworks must be created to govern the actions of both

AI vendors and educational institutions, ensuring adherence to ethical standards and protecting educational outcomes.

8.2.2 For teacher education institutions

Educational curricula should deliver comprehensive AI literacy and ethics training for both pre-service teachers and mentors, empowering them to engage responsibly with emerging technologies. Collaborative communities of practice (CoPs) must be fostered to integrate AI tools into WIL while preserving the centrality of human relational dynamics. Furthermore, AI tools must be developed and applied to be culturally responsive, inclusive, and accessible, ensuring relevance and equity across diverse educational contexts (Bulathwela et al., 2024).

8.2.3 For EdTech developers

The use of AI systems in education must incorporate a design for adaptability, transparency, and an equitable focus on learners from different linguistic backgrounds, as well as contextual customisation to accommodate the varied needs of students. Close working relationships are needed between educators and developers of AI so that the development of AI technologies is aligned with educational goals, thereby enhancing instructional quality (Darling-Hammond & Hyler, 2023). Developers of AI systems must create ethical safeguards, including minimising the collection of student data, employing strong protocols to protect student privacy, and auditing for systemic biases, all to provide a framework to assure the appropriate use of AI in the classroom.

8.2.4 Equity and access

To create a more equitable environment for the use of AI in education, institutions need to begin by eliminating the "digital divide" through the creation of reliable infrastructure that includes the availability of the internet and devices, ensuring all teachers and students can access AI resources (Qayyum et al., 2025). Next, institutions will need to establish mechanisms for ongoing assessment of equity; these assessments would measure the equity of AI tool implementation across different learner populations to help identify and mitigate inequity in access to educational opportunities.

8.2.5 Innovation and continuous improvement

To provide an environment that is both supportive and ethically equitable regarding innovative early childhood educational practices through collaborative research and partnerships, institutions must foster relationships with other educational entities, technology developers, and researchers to design and evaluate rigorous and effective uses of AI as a tool for educators (Darling-Hammond & Hyler, 2023). Additionally, institutions can create an environment of reflective practice by encouraging educators to examine how they use AI in the classroom, share their reflections, and develop collective approaches to best utilise these new forms of technology. Ultimately, institutions must be aware of emerging trends in AI and its relationship to education and adapt their policies and practices to incorporate and responsibly develop new technologies and knowledge in the most efficient and productive way possible.

8.2.6 For researchers

To responsibly implement AI into early childhood education, we need to develop a longitudinal research agenda that evaluates how AI-mediated work integrated learning affects both teacher development and equity outcomes over time. We must also explore the potential for cross-cultural and multiple contextual uses of AI to ensure its applicability is as wide as possible across all educational contexts. Additionally, to address technology-driven bias in AI use and to allow for participatory oversight while ensuring fairness, accountability, and inclusion in AI deployment, we must establish robust ethics frameworks and governance structures (Berson et al., 2025).

8.3 Concluding Remarks

Integrating AI into early childhood teacher education presents both challenges and opportunities. When approached strategically, with equity, ethics, and relationality at the forefront, AI can enhance reflective practice, mentoring, and innovative practices through WIL. However, in the absence of thoughtful strategies, AI risks exacerbating existing discrepancies and ethical blind spots (Ngcobo & Mpofu, 2024). This chapter provides a theoretical and empirical foundation for AI integration, a conceptual framework (RAIIF) for operationalisation, and strategic recommendations for diverse stakeholders. Overall, the chapter underscores the importance of bridging AI, equity, and innovation to cultivate responsible, inclusive, and transformative ecosystems in teacher education.

This chapter is limited by its small sample size and its focus on a single province in Zimbabwe. The findings are not intended to be statistically generalisable but rather to offer contextualised insights and a transferable conceptual framework. Furthermore, the rapid advancement of AI technologies means that the specific tools discussed may become obsolete; nonetheless, the principles of the RAIIF are expected to remain relevant in the future and promote the implementation of innovations.

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CHAPTER EIGHT

Applied Research Projects as Work-Integrated Learning in Zimbabwean Teacher Education: A Conceptual Analysis

Kudakwashe Manokore
Department of Art, Design and Technology,
Faculty of Science and Technology Education,
National University of Science and Technology, Bulawayo, Zimbabwe
Doris Chasokela
Department of Technical and Engineering
Education and Training, Faculty of Science and Technology Education,
National University of Science and Technology, Bulawayo, Zimbabwe
Corresponding author: Kudakwashe Manokore (kudakwashe.manokore@nust.ac.zw)

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Abstract: Worldwide, work-integrated learning (WIL) is a central component of teacher education. This is traditionally facilitated through teaching practice, which allows student teachers to apply theoretical knowledge in authentic classroom contexts. In the Zimbabwean context, universities often complement teaching practice by assigning students to individual supervised research projects at the undergraduate level. The aim is to synthesise existing knowledge to develop new conceptual insights and critically examine how applied research projects, as a form of WIL, can be effectively and ethically integrated into contemporary teacher education. This chapter employs a qualitative desk-based research design to explore applied research projects as a form of WIL in in-service teacher education within Zimbabwean universities. Drawing on the principles of experiential learning theory (ELT), the analysis argues that applied research projects provide meaningful work-integrated learning experiences by actively engaging student teachers and have the potential to enhance teacher preparation. However, the evolving integration of Generative Artificial Intelligence (GAI) into higher education introduces several new pedagogical and ethical challenges for applied research as WIL. While GAI tools can support the research processes, their misuse may lead to academic dishonesty, including the presentation of fabricated problems or findings, thereby undermining the development of professional and problem-solving skills. This situation underscores the necessity for clear institutional guidelines to promote authentic learning. The chapter contributes to ongoing debates regarding the strengthening of WIL in teacher education.

Keywords: Applied research projects, generative artificial intelligence, work-integrated learning, experiential learning.

1. Introduction

Work-Integrated Learning (WIL) is a comprehensive term encompassing various approaches aimed at the practical and experiential development of knowledge, enabling students to gain appropriate access to work-related activities relevant to their fields of study. Stirling, Kerr, Banwell, MacPherson, and Heron (2016) observe that WIL is frequently used interchangeably with other terms, including work-based learning, practice-based learning, work-related learning, vocational learning, experiential learning, cooperative education, clinical education, internships, practicums, and field education. These approaches involve systematic training models in which apprenticeships, as the primary locus of learning, are situated within the workplace. They also incorporate formalised workplace experiences integrated into postsecondary programmes encompassing work experience, professional practice, cooperative education, internships, and on-the-job training, alongside institutional partnerships with work sites, aimed at producing broader industry or community-facing projects, such as service learning. Institutions such as the National University of Science and Technology (NUST), the University of Zimbabwe (UZ), the Zimbabwe Open University (ZOU), and Midlands State University (MSU) utilise some of these methodologies within their teacher training programmes.This expansive interpretation acknowledges the adaptability of WIL delivery modalities and their applicability across various disciplines.

In the context of teacher education, teaching practice (TP) and applied research projects represent significant WIL modalities that integrate academic literature with the practical realities of teaching. By engaging in these activities, student teachers are afforded opportunities to operate in authentic classroom and school environments, apply theoretical knowledge, develop professional competencies, and engage in reflective and inquiry-based practices. Nevertheless, the increasing incorporation of artificial intelligence (AI) within educational processes, particularly in research and assessment, introduces challenges necessitating well-defined and practical regulatory frameworks. A primary concern regarding the utilisation of AI is the potential for breaches of academic integrity, whereby students may exploit these technologies to complete assignments that are intended to foster skill development (Bala and Colvin, 2023). The Open Innovation Team and the Department for Education (2024) highlight growing apprehensions regarding generative AI (GAI)-facilitated academic malpractice, the dependency of students on AI tools, and the associated ethical, safety, and data privacy implications. Such tools may inadvertently promote cheating, excessive reliance on automation, and a potential erosion of educators' involvement, contributing to academic dishonesty (Almpanis et al., 2025; Mukwerete and Chikusvura-Matiza, 2025; Matarazzo et al., 2025; Nikolopoulou, 2025; Osunbunmi et al., 2024). Furthermore, they caution that the use of GAI tools may present risks to the integrity of assessments, potentially resulting in misleading indications of learning and exacerbating issues surrounding academic integrity. GAI may similarly undermine traditional assessment practices at higher education levels (Nyaaba and Zhai, 2024; Bala and Colvin, 2023). Additionally, GAI models are capable of generating plausible yet false academic references and other citations (Bala and Colvin, 2023).

While scholars like Matarazzo et al. (2025) highlight standardised AI integration processes, monitoring, transparency of AI models, and explainable artificial intelligence (XAI) to ensure the reliability of the content, protect data and access, and establish the credibility of AI-as-assessment practice, it has been well studied that the concerns about the application of GAI in higher education are many. GAI can only deepen this dilemma further by compounding existing educational disparities. The situation raises the need to critically question how the use of applied research projects as WIL could be done in a meaningful and ethical way in Zimbabwean higher education. Thus, this chapter, located within today's landscape of prevalent GAI application in both education and research, illuminates the risks and rewards associated with introducing promising technologies into the context of teacher education models developed in Zimbabwean universities.

1.1 Problem statement

In the Zimbabwean teacher education context, promoting authentic learning, academic integrity, and the development of critical skills is crucial amidst growing concerns about the increase in plagiarism, the availability of GAI tools, and AI-assisted dishonesty by student teachers. These apprehensions are compounded by the potential for GAI to generate and write complete research projects that are difficult to distinguish from those created by humans. Rather than identifying real-world educational problems, investigating them, and proposing plausible solutions, some student teachers resort to plagiarism and present fictional research problems and solutions, undermining the development of critical thinking, creativity, and interpersonal skills. This overly threatens the development of essential professional competencies in student teachers. The boundaries of authorship, assessment, and inquiry-based learning experiences inherent in applied research projects are being redefined in real time. Against this background, the chapter critically examines how applied research projects, as a form of WIL, can be effectively and ethically integrated into contemporary teacher education. The following research questions guided the study:

- What is the relationship between applied research projects as WIL and experiential learning theory?
- What is the role of applied research projects as WIL in enhancing teacher preparation in contemporary context of widespread GAI use in learning and research in Zimbabwe?
- How are teacher education institutions, departments and scholars in Zimbabwe responding to the increasing accessibility and integration of generative AI technologies?

1.2 Conceptual framework

The study utilises experiential learning theories and experiential education as two conceptual frameworks to examine the potential for applied research projects to function as Work-Integrated Learning (WIL) experiences. These perspectives are particularly relevant as the study focuses on the integration of academic knowledge, professional practice, and real-world problem-solving in teacher preparation programmes. Experiential learning theory posits that learning is shaped by direct experience and reflective engagement with that experience. The Association for Experiential Education (n.d.) defines experiential learning as "a process in which learners are immersed within the concrete world to engage with it" [2]. Experiential learning is commonly understood as learning through doing or learning through experience, emphasising the active role of the learner in acquiring knowledge and making sense of information. This study is underpinned by Kolb's Experiential Learning Theory (ELT), which suggests that learning occurs in four interconnected stages: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. Student teachers engage in authentic experiences, reflect on these experiences, develop conceptual understanding, and apply this understanding to new contexts. This cyclical process closely mirrors the stages involved in applied research projects. For instance, a student teacher's concrete experience may involve identifying a genuine research problem in their classroom or real educational challenges. Reflective observation occurs as the student reviews literature and reflects on their experiences to comprehend the issue. Abstract conceptualisation takes place as they collect, analyse, interpret data, and devise intervention strategies and models. Finally, active experimentation involves reflecting on findings and applying new ideas and strategies to improve practice. The integration of theory and practice is essential in education, where practice is purposefully integrated into theory through direct observation and reflection (Kolb, 2014).

TP and applied research projects in the field of teacher education are work-based learning experiences that are reflective of the principles of experiential learning. According to contemporary scholarship, experiential learning theory and experiential education continue to be relevant in universities and professional education. Green et al. (2024) assert that experiential learning is a constantly evolving field that values active participation in genuine situations and opportunities over passive knowledge. They identify the part that theory plays in the purposeful weaving together of practice, reflection and application design in a learning setting. This results in enhanced learning and integration between academia and industry practice. For example, NUST, UZ, ZOU and MSU teacher education models that reflect ELT in the form of TP or school attachment models. Student teachers practice in schools and teach real classes, reflect on their own lesson delivery, develop teaching principles to improve learner engagement and adjust future lessons using acquired ideas.

Through real classroom and school context, these WIL experiences have certain benefits. Student teachers are able to engage in meaningful academic applications, gain professional capability, and engage in reflective and inquiry learning. It is proven through research that such techniques help close the theory-practice divide through developing pedagogical knowledge, professional judgment and adaptive expertise (Bertram & Rusznyak, 2018; Ferns et al., 2021; Griffiths & Tann, 2019; Jackson & Bridgstock, 2021; Rusznyak & Bertram, 2020). ELT thus offers a coherent theoretical model guiding how applied research projects, implemented as WIL, can contribute to teacher education. It's a model for thinking about how student teachers learn through experiences, reflection and inquiry. This is especially true in modern educational contexts influenced by technological change and the growing use of GAI.

2. Materials and Methods

This chapter presents a conceptual analysis that employs a qualitative, desk-based research design. The analysis is grounded in a review of both academic and grey literature pertaining to WIL, teacher education, and GAI. Literature was selected through a transparent search strategy, which included file probing, keyword definition, and staged screening at the levels of title, abstract, and full text. Key databases, including ERIC, Scopus, and Google Scholar, were searched using terms such as 'work-integrated learning,' 'applied research,' 'teacher education in Zimbabwe,' and 'generative AI in education,' with purposive sampling utilised to retain conceptually rich sources. The authors supplemented this analysis with documentary examination of Zimbabwean education policy documents (e.g., the 2015-2022 Curriculum Framework and Education 5.0 Zimbabwe) and drew upon their professional experiences within Zimbabwean teacher and higher education to contextualise the findings. The analysis was guided by the principles of experiential learning theory, with the aim of synthesising existing knowledge to develop new conceptual insights.

3. Contextualising the Landscape

3.1 Forms of work-integrated learning

WIL is connected with a wide range of practices and pedagogies that aim to link scholarly learning to practice. It is informed by learning theories such as experiential learning, service learning, cooperative education, and curriculum design through internships, fieldwork, engineering sandwich courses, clinical placements, teacher practicums, work placements, simulations, case studies, project-based learning, and volunteering. While these models do not necessarily require placements in an actual work environment or community, such placements are typically assumed (Sachs et al., 2017). For example, teacher education models in Zimbabwe that align with some of these approaches include UZ’s teaching practicum (a school-based model), MSU’s internship or school attachment model, ZOU’s service learning model, teachers’ colleges' microteaching and simulation models, and project-based learning models in all teacher training institutions.

In the South African context, WIL has been further defined in terms of workplace-based learning, work-based experience, experiential learning, and cooperative education (Mesuwini et al., 2023). According to Universities Australia (2019), while work placements remain the predominant model of WIL, institutions in higher education increasingly incorporate components not found in placement models, including projects, simulations, and fieldwork. These may take the form of volunteering, live performances, mentoring, case-based learning, or hands-on work specifically conducted in workplace settings. Collectively, these approaches reflect a shift towards more flexible and representative models of theory and practice within higher education. For example, Zimbabwean teacher education models that embody WIL in the form of cooperative education, fieldwork and community engagement, and mentoring-based models are employed by GZU, ZOU, and various Zimbabwean schools, respectively.

3.2 Zimbabwe's university teacher education system

Bachelor of Education (B.Ed.) and postgraduate-level teacher education qualifications are offered by universities throughout Zimbabwe. Programmes include core educational theory and foundations, professional studies (such as ethical education, educational management, and reflective practice), subject-specific pedagogy, assessment, research methods, information and communication technologies, supervised TP, and a research project. In this context, school-based TP is a significant aspect of teacher education in Zimbabwe, where student teachers spend time primarily in actual classrooms (Mukeredzi & Manwa, 2019). This involves training student teachers to teach through experiential learning in real school settings, allowing them to transfer theoretical ideas to practical situations. Matsa and Chikunda (2024) argue that TP is a necessary component of teacher education, as it familiarises student teachers with actual classroom practice. During this time, student teachers receive assistance in their learning experiences, develop their teaching practices concerning instructional methods, classroom management, and professional dispositions, and engage in reflective practices regarding their interactions and self-assessment. Students are required to compile portfolios of their teaching, which include documentation files and logbooks that track their professional work. Both pre-service and in-service teachers, as well as those involved in professional development programmes, are formally assessed during this period.

In current teacher training curricula, TP is also aligned with applied research projects or dissertations that provide students with the opportunity to apply educational theory in real-world contexts. These applied research engagements motivate teaching practice through inquiry and reflection, promote critical thinking, and enable student teachers to seek improvement in their teaching and learning practices as part of their professional development. Research on teacher education, therefore, functions not only as an application of theoretical knowledge but also as the development of a reflective and inquiry-oriented professional disposition aimed at continually enhancing educational practice (Al-Thani & Ahmad, 2025; Tsafos, 2025). While TP is of great importance, it is most often practised in the classroom, where teaching is largely assessed through observations of lessons. This can hinder the development of broader skills, including competence-based education, education for sustainable development, and other 21st-century skills that are relevant both inside and outside the classroom (Matsa & Chikunda, 2024). Current TP must move beyond mere content teaching to address the significant challenges facing society today. Therefore, student teachers are encouraged to employ diverse methods, strategies, and skills from their prior knowledge to create meaningful, relevant, and context-responsive learning experiences.

3.3 Applied research projects delivered through WIL

The applied research projects are a major feature of WIL, merging scholarship with practical application. Unlike pure theorisation, this literature addresses the application of existing knowledge, specifically the study of particular procedures and methods for knowledge transfer. The student teacher identifies educational problems and researches them scientifically to develop a logical investigation that leads to applied and practical solutions. Sachs et al. (2017) state that students in WIL-based projects achieve this by working productively and collaboratively, critically analysing the data and information they gather, writing papers, and expressing their findings in structured texts. These projects train students to be resourceful and creative, from the idea generation and proof-of-concept phase to prototyping and testing, ultimately providing solutions to contemporary problems.

In certain types of applied research and learning, end-users and researchers are connected to organisations early in their product or service development process, allowing for the exploration of new ideas and the study of their influence. Sometimes, in teacher education, an applied project will be used to bring together student teams from various fields, including education, business, design, engineering, and information technology, to address externally funded problems. Such initiatives already exist within working environments or at local universities and are becoming increasingly interdisciplinary and collaborative. They foster cooperation among academic institutions, host schools or organisations, teachers, and students, contributing to a high level of educational attainment. Evidence suggests that there are associations between these applied research projects and enhanced collaborative abilities, improved metacognitive tendencies, self-concept, self-efficacy, and learner initiative among both teachers and students (International Development Research Centre, 2024; Johari et al., 2022; Ryan & Deci, 2020).

3.4 Teacher professional development and applied research

Teacher education research, however, is unequivocal that the most effective strategies for enhancing student outcomes rely on teachers' ability to implement a pedagogy that emphasises learning (International Development Research Centre, 2024). This indicates that traditional learning approaches require a paradigm shift towards a more student-centred approach, necessitating that teachers acquire relevant competencies to better meet the needs of new-age classrooms, which are increasingly heterogeneous. Consequently, recent teacher professional development (TPD) programmes have emerged as the most effective response to modern educational challenges. Unlike traditional workshop-based approaches, these programmes focus on interactive, cross-professional, collaborative, technology-rich, and context-bound learning experiences (Darling-Hammond, 2025; Fütterer & Runge, 2025; International Development Research Centre, 2024). In Zimbabwe, TPD has developed in response to curriculum reform, limited resources, and the need for professional learning in this domain. It advocates for an emphasis on building practice-based, collaborative, school-based, and practice-oriented approaches without relying on externally provided workshops (Ministry of Primary and Secondary Education [MoPSE], 2015; Mtetwa, 2014; Mukeredzi & Manwa, 2019). In this context, continuous applied research is emphasised within WIL frameworks.

3.5 Generative artificial intelligence (GAI)

GAI has emerged as a transformative force in education, offering opportunities to personalise learning, enhance accessibility, and support iterative feedback processes. Bala and Colvin (2023) argue that GAI provides tailored learning environments for users with diverse needs, assisting with tasks such as coding and creative composition. In higher education, GAI systems have the potential to alleviate the substantial workload of educators by incorporating various instructional methods, including traditional techniques and innovative formats; the current assessment processes are supportive of these approaches (Gravino et al., 2024). Simultaneously, GAI introduces numerous new features, such as AI-enabled quizzes and dynamic feedback mechanisms, which are indispensable for personalised teaching. Kumar et al. (2024) point out that GAI can analyse vast amounts of educational data, providing valuable insights to inform instruction, curricular design, and institutional policy. For learners, GAI can function as a tailored tutor, assisting students with course comprehension, exam preparation, and skill development, thereby promoting greater equality in learning opportunities (Gravino et al., 2024). Matarazzo et al. (2025) further suggest that while AI and GAI present significant potential for personalised and inclusive education, they also raise critical ethical, pedagogical, and equity issues that must be addressed.

In applied research, GAI tools facilitate the writing process for students, encompassing planning, outlining, editing, and personalised feedback. However, when GAI is employed to generate text, issues of attribution, academic integrity, and the consideration of independent academic skills also arise. The use of reference-management applications such as Zotero, Mendeley, and EndNote to collect research materials and generate citations is becoming increasingly prevalent. According to the Open Innovation Team and the Department for Education (2024), GAI is being utilised by students for various tasks, including researching topics, summarising materials, transcribing, translating, and proofreading. Nevertheless, while GAI offers considerable advantages, academics caution against its uncritical adoption. Fodouop, Kouam, and Muchowe (2025) issue a warning regarding the risks associated with academic integrity, the displacement of academic labour, and the reinforcement of existing biases due to GAI. Similarly, Kumar et al. (2024) emphasise the necessity for human supervision, data privacy, and ethical considerations. The Open Innovation Team and the Department for Education (2024) note that AI text-detection tools are unreliable, with systems such as OpenAI's text classifier being withdrawn due to low accuracy. As Kahn et al. (2025) contend, distinguishing between AI-generated and human-authored text is increasingly challenging, and educators are being tasked with designing assessment practices that prioritise learning processes over product-based evaluation.

4. Discussion of Findings

4.1 Applied research projects, WIL and ELT

In Kolb's (1977) ELT, which forms the basis of numerous empirical studies, it is argued that learning occurs in a loop comprising concrete experience, reflective observation, abstract conceptualisation, and active experimentation. At its most elementary level, the research process involves identifying the underlying problem that connects research to the actual environment, reviewing relevant literature, designing a research method (i.e., a practical experiment, survey, or prototype), collecting and analysing data, finding a solution to the problem, and making recommendations for practical application or further study (Creswell & Creswell, 2018; Kumar, 2021). The stages of experiential learning delineate the types of experiences involved in such learning and explain why these experiences are necessary, enabling student educators to carefully plan tailored activities for genuine practice learning. Experiential learning is not merely the art of observation; rather, it is the science of interaction and expression.

Consequently, the practices of the applied research process are specific to student teachers in the WIL context. It begins by identifying a problem within a realistic classroom or school setting, where research is directed towards an area of concern, ensuring that the empirical research aligns with real professional practice (Dika et al., 2025). A thorough literature review allows student teachers to critically explore previous studies, determining which solutions are inadequate and where additional research is warranted (Dika et al., 2025). An appropriate research methodology—whether qualitative, quantitative, or mixed-methods—will provide methodological rigour as well as enhance research literacy. Systematic data gathering and analysis also encourage student teachers to develop their abilities in analysing and evaluating practices for evidence-based decision-making. Action research and design-based research principles inform subsequent steps in applying proposals or conducting tests to help develop, deliver, and evaluate interventions in the field, thereby improving practices beyond mere theory (Ozer et al., 2023). Finally, the recommendations provide student teachers with a framework for translating research findings into practice, fostering innovation in curriculum design or further development of research processes. In the field of education, applied research projects are often integrated into service learning, cooperative education, curricular planning measures, teacher practicums, simulations, case studies, and so on. These projects further clarify the interplay between theory, research, and practice, thereby reinforcing the argument for using research as a core methodology in teaching within the WIL context (Mutambara, 2023).

Despite the pedagogical benefits brought by digital and AI-augmented tools, the field of GAI and the incorporation of applied research in general education present new challenges. GAI must be embedded within educational research and assessment processes; its use and misuse, as well as over-reliance, should be mitigated, and the risk of academic dishonesty should be minimised through proper training and institutional protocols (Matarazzo et al., 2025). This implies concerns regarding academic integrity violations, pedagogical impacts, and over-reliance. A significant question that emerges from GAI in education is whether the processes that generate information contribute to false or misleading content (also known as "hallucinations") or reinforce societal prejudices and discriminatory beliefs (Gravino et al., 2024). GAI is increasingly utilised as a pedagogical resource, assessment tool, instructional design assistant, and academic integrity tool by teachers and student learners for specific assessment tasks, knowledge construction, and general learning activities. Mukwerete & Chikusvura-Matiza (2025) elaborate that AI implementation in higher education within Zimbabwean educational contexts has led to increased support for students through AI applications, but this has also resulted in detrimental impacts such as plagiarism and decreased student creativity, primarily due to poor accountability and weak rules or regulations. Among the normative issues involving GAI in education are algorithmic bias, transparency and accountability concerns, equity of access, privacy and security issues, and copyright infringement (Osunbunmi et al., 2024; Bala & Colvin, 2023). Matarazzo et al. (2025) identify one of the ethical questions as pedagogical dilemmas regarding the use of GAI in education. Ethical issues include data privacy and model bias, reliance on the system, and concerns about misinformation and AI-generated inaccuracies that compromise the credibility of educational content. Mismanagement of GAI weakens student teachers' applied research projects by misrepresenting engagement across Kolb's ELT cycle, leading to superficial experiences, uncritical reflection, weakened conceptualisation, and less authentic application.

4.2 Institutional responses

The adoption of AI for assessing student applied research raises fairness and equity issues, as biases and prejudices can influence assessment results. However, assessment design needs to address these concerns. On one hand, AI may lead to more personalised learning and mastery for students; on the other hand, it could result in deficiencies in critical thinking, creativity, and problem-solving skills. As a result, at this stage a big question arises how to balance the advantages and disadvantages of AI-enabled learning while ensuring a continued focus on quality, human-centred teaching approaches? In this context, guidelines are increasingly important to clarify instructions that can be applied to teacher practice, recognising student use of AI and treating AI as a constructive tool against AI-enabled academic malpractice

The Open Innovation Team and the Department for Education (2024) recommend a government response that targets research resources and develops curricula in response to the impact of AI on education. Bala and Colvin (2023) propose three policy measures to regulate Generative AI (GAI) in assignment coursework: prohibiting its implementation when it counteracts basic learning; allowing its deployment only with clear responsibilities in mind; and promoting its application to support higher-order learning, creativity, and critical thinking. GAI does not offer a universally applicable institutional response. Other institutions have sought to prevent the implementation of GAI through bans and policy or technical measures, but none have been effective, particularly as technology for GAI tools becomes increasingly accessible. These measures have not led to widespread adoption or monitoring, resulting in more nuanced approaches to piloting approved tools, managing risk, or providing flexibility for educators without a solid institutional foundation (Open Innovation Team & Department for Education, 2024). Although Zimbabwean universities operate with a degree of autonomy, teacher education currently reflects weakly regulated, flexible GAI use, with the most feasible and effective response being guided integration supported by clear accountability, rather than prohibition or resource-intensive control systems.

As such, tackling AI-induced academic malpractice should be inclusive in nature, involving new forms of evaluation, expanded invigilation, policy clarity, staff development, and oral exams or vivas (Open Innovation Team & Department for Education, 2024). It is recommended that further action and transparency in the use of GAI are also implemented in this process of learners' improvement, which may include AI assistance in recognising, summarising, brainstorming ideas, or generating initial lists of resources to be systematically and critically scrutinised and documented (Bala & Colvin, 2023). Similarly, Matsa and Chikunda (2024) suggest that for teacher education to be effective, research-informed pedagogies coupled with exercises to encourage the development of student teachers (reflective practitioners, responsible researchers, and technology users) in their classrooms should be applied. European organisations are also calling for the responsible application of AI systems in educational tasks globally, with the right measures, policy frameworks, capabilities, and regulatory and experimental academic research and laboratories to ensure such activities are used responsibly (Gravino et al., 2024). Though this intervention represents a shift from unregulated and ineffective control of GAI towards a structured, pedagogy-driven model, it needs adaptation to fit Zimbabwe's resource-constrained higher education context. Moreover, research is still needed to address certain areas (e.g., ownership of intellectual property of the outcomes of AI and the sustainability of the educational publishing ecosystem) (Open Innovation Team & Department for Education, 2024).

5. Conclusions

With GAI's strategic support, TP and applied research hold great potential as forms of WIL in teacher education in Zimbabwe. These modalities promote service learning, cooperative educational environments, and curriculum development by fortifying the alignment of theory, research, and professional practice. In response to legitimate challenges faced by students in school and community contexts, applied research projects enable student teachers to put pedagogical theory into practice in a context-appropriate manner. However, the application of GAI is fraught with significant risks due to its uncritical or inadequately managed incorporation. Academic dishonesty can occur through the misuse of GAI tools, making it challenging for teacher educators to verify the authenticity of students' applied research. Some student teachers may also plagiarise or invent fictitious research problems and solutions. Consequently, students may engage superficially with applied research, hindering their development of essential skills such as interpersonal skills, creativity, critical thinking, and problem-solving. On a larger scale, robust governance mechanisms are crucial to ensuring that the educational value and integrity of AI-supported applied research projects as WIL are maximally utilised. Such frameworks can include systems for monitoring and evaluation, transparent AI models, standards for AI integration, and XAI frameworks. This approach is vital for safeguarding data protection, ethical research practices, equitable access, and the credibility of content. Ultimately, this can position applied research projects as authentic, credible, and sustainable WIL strategies in Zimbabwean teacher education.

Despite the relevance of the findings, this study is constrained by a number of methodological and contextual limitations. As a conceptual analysis, this chapter does not provide empirical evidence for the claims made. The findings are interpretive and should be validated through primary research. Furthermore, the analysis focuses on a single theoretical perspective, ELT, and may not capture the full complexity of WIL and GAI integration. Despite these limitations, this work contributes significant information regarding TP and applied research endeavours.

5.1 Recommendations and future directions

Much more is required to examine the impact of applied research projects as WIL in teacher education in Zimbabwe. This will activate student teachers' competencies as professionals, enhance reflection, and prepare them for classroom realities. Future research should employ a design-based approach to co-develop and test a context-sensitive framework for GAI use in applied research projects, involving a cohort of student teachers and their mentors in Zimbabwean universities. This could inform and experiment with context-sensitive frameworks for ethical and pedagogically sound GAI implementation in applied research endeavours moving forward. Such frameworks should emphasise not only academic integrity and respect for authenticity in university students' work but also the advancement of higher-order thinking skills. However, issues related to heavy dependence on AI as content generators, fabricated research outputs, plagiarism, and fake results generated by AI must be addressed. Mixed methods and quasi-experimental approaches, supported by case study or action research designs to capture the contextual and practical realities of implementation, can be employed to evaluate the success of professional development programmes. Such programmes can subsequently be designed to enhance educators' ability to supervise applied research while using AI tools responsibly. Even though this approach addresses aspects of learning AI in Zimbabwean teacher education, further work is needed to comprehend what the wider implications of applying Explainable AI (XAI) principles would be in facilitating transparency in assessment and guided decision-making in Zimbabwean teacher education.

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CHAPTER NINE

Reimagining Work-Integrated Learning in Rural School Contexts: Harnessing AI for Equitable Professional Development

Bafundi Zealous Mapisa
Continuing Professional Teacher Development,
Faculty of Education, IYunivesithi Walter Sisulu, Mthatha, South Africa
Limkani Sincuba
Continuing Professional Teacher Development,
Faculty of Education, IYunivesithi Walter Sisulu, Mthatha, South Africa
Corresponding author: Bafundi Zealous Mapisa (bmapisa@wsu.ac.za)

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Abstract: Work-Integrated Learning (WIL) is essential for the professional preparation of student teachers; however, persistent inequalities in rural areas hinder access to mentorship and professional development. This qualitative case study, grounded in Critical Pedagogy, examines how the integration of Artificial Intelligence (AI) into work-integrated learning (WIL) can promote equitable professional development within teacher education in South Africa's Eastern Cape Province. A purposive sample of 30 participants, including Heads of Department, teaching practice supervisors, and student teachers, engaged in semi-structured interviews and focus group discussions as data collection methods. The data were analysed thematically. The findings revealed that AI-supported WIL enhances access to mentorship and professional development by expanding networks and facilitating feedback in isolated settings. Additionally, the study highlighted those structural, ethical, and contextual factors, such as infrastructural inequities and data governance, significantly influence the implementation of AI-supported WIL. The study concluded that the use of AI tools necessitates critical, relational, human-centred supervision. Furthermore, it emphasised the importance of involving rural educators in the design of AI-supported systems to ensure relevance and maintain pedagogical integrity. The study recommended that teacher education institutions should critically focus on enhancing digital infrastructure in rural areas to establish robust ethical governance for AI and adopt hybrid mentorship models. These recommendations elucidate how AI can substantially improve equitable, human-centred work-integrated learning (WIL) in rural teacher education.

Keywords: Artificial intelligence, equitable, harnessing, professional development, reimagining.

1. Introduction

Work-Integrated Learning (WIL) is a fundamental pedagogical approach in teacher education, bridging the gap between classroom theory and practical experience in real school settings. In the Eastern Cape Province of South Africa, characterised by rural schools, limited resources, and inconsistent digital infrastructure, WIL is essential for preparing student teachers to navigate the complex and context-specific realities of the classroom (Du Plessis & Dreyer, 2024). However, the rapid rise of Artificial Intelligence (AI) as an educational tool has introduced both new opportunities and challenges for WIL (Hadzic, 2024).

Exploring AI-enhanced WIL in rural teacher education is important for two key reasons. Firstly, AI-driven professional development can help alleviate geographic isolation by connecting rural educators with broader professional networks and providing just-in-time learning resources (Fidalgo & Thormann, 2024). Secondly, the integration of AI into teacher education raises critical discussions regarding equity and pedagogical integrity (Karataş & Yüce, 2024). Recent empirical research and reviews have focused on AI applications for teacher professional development and classroom support, reflecting a growing interest and emerging evidence for customised, AI-assisted learning (Hu, 2024; Nazaretsky et al., 2022). As AI continues to advance, it becomes essential to investigate how it can be effectively utilised within WIL to uphold human-centred values (Hadzic, 2024).

Recent research highlights the transformative potential of AI in education, particularly in personalising learning and enhancing mentorship (Hwang et al., 2020; Preiksaitis & Rose, 2023). However, these benefits are not universally realised and depend on factors such as digital infrastructure and ethical governance (Hadzic, 2024; Nguyen et al., 2023). Digital inequality, encompassing data privacy, algorithmic bias, and the erosion of mentorship, is especially salient in under-resourced rural areas (Joyce et al., 2021; Langeveldt & Pietersen, 2024a, 2024b). AI systems are often designed for urban contexts, limiting their effectiveness in rural settings without adaptation (Bircan & Özbilgin, 2025; Min, 2023). In South Africa's rural education, particularly in the Eastern Cape, challenges such as poor infrastructure and connectivity hinder access to AI-supported professional learning (Fobosi & Malima, 2025; Mokoena & Seeletse, 2025). Therefore, AI could exacerbate the marginalisation of rural educators (Nguyen et al., 2023; Hussein et al., 2025).

Digital exclusion among rural educators in South Africa raises ethical concerns about data privacy, algorithmic bias, and the depersonalisation of mentorship in AI-driven WIL models (Acharya et al., 2025; Essien et al., 2022). This study explores how AI can enhance hybrid WIL models by focusing on AI innovation, human-centred learning, and social justice. This qualitative case study at a rural university in the Eastern Cape examines the experiences of Heads of Department, teaching supervisors, and student teachers involved in AI-supported WIL. By prioritising participants' perspectives, it highlights AI's potential to expand access to mentorship and addresses ethical challenges in under-resourced settings, contributing to discussions on equitable practices in teacher education (Joyce et al., 2021).

The study was guided by these research questions:

- How does the integration of Artificial Intelligence (AI) into Work-Integrated Learning enhance access to mentorship and professional development for rural educators?
- How do structural, ethical, and contextual conditions shape the implementation and use of AI-supported Work-Integrated Learning in rural teacher education?

2. Literature Review

WIL and teacher professional development (TPD) have traditionally occupied a significant position at the intersection of formal education and workplace practice, as well as in authentic assessment (Ghamrawi et al., 2024). The emergence of Artificial Intelligence (AI) within the educational landscape has introduced innovative possibilities, such as adaptive tutoring, automated formative feedback, and analytics-driven recommendations, which hold the potential to enhance mentorship and professional learning beyond geographical limitations (Amo-Filva et al., 2023; Koukaras et al., 2026). Nevertheless, the rapid implementation of AI also raises critical concerns regarding equity, contextual relevance, and ethical governance, particularly in rural and resource-constrained environments.

2.1 AI-supported WIL and the enhancement of mentorship and professional development

In teacher education, AI-supported platforms have been demonstrated to enhance formative feedback related to lesson planning, teaching practices, and reflective journals. This capacity bolsters the developmental dimensions of WIL, particularly in contexts where human supervision is limited due to geographical distance and substantial workloads (Billett, 2025; Brandão et al., 2024). AI plays a pivotal role in professional development within WIL by facilitating personalised learning pathways and connecting student teachers to broader professional communities. Through recommendation systems, automated feedback tools, and analytics-supported reflection, AI can promote self-directed professional growth and sustained engagement in mentorship, especially in rural and under-resourced settings (Hwang et al., 2020; Preiksaitis & Rose, 2023). It is essential to view AI not as a substitute for mentorship but as an enabling tool that enhances access to mentorship and professional learning opportunities within WIL.

2.2 Challenges and ethical considerations in AI-supported WIL

The existing literature highlights four interconnected areas of concern that influence the governance of AI in WIL:

2.2.1 Infrastructural inequities and the digital divide

Recent studies highlight disparities in connectivity and device availability in rural South Africa, which limit access to AI platforms (Dyantyi & Mkabile-Masebe, 2025). Inconsistent bandwidth and a lack of devices may result in AI solutions overlooking the educators they aim to assist

(Badshah et al., 2023), raising concerns that AI could reinforce existing inequities without targeted infrastructure investment (Dyantyi & Mkabile-Masebe, 2025). Research emphasises infrastructural inequities as barriers to the efficient integration of AI in low-resource education (Dyantyi & Mkabile-Masebe, 2025; Langeveldt & Pietersen, 2024). Policy analyses indicate that most AI systems are designed for higher-resource environments, which are rarely found in rural schools within the Global South (Katende, 2025; Walker, 2024). Inconsistent infrastructure risks exacerbating educational inequalities by benefiting those with existing digital capital (Begum & Gul, 2025; Facer & Selwyn, 2021). This study, drawing on Critical Pedagogy, examines infrastructure as a power dynamic that affects participation and agency in professional learning. Exploring participants' experiences in rural WIL placements underscores how infrastructural inequities shape the effectiveness and accessibility of AI-enhanced mentorship in rural South African teacher education.

2.2.2 Data privacy, ownership and governance

AI ethics in education emphasise transparency, consent, and accountability due to extensive data collection by AI systems, which raises concerns regarding data control and its benefits (Mohseni et al., 2021; Zha et al., 2025). The risk of opaque "black-box" models impacting professional judgments is particularly pronounced in weak regulatory environments (Mohammed & Malhotra, 2025; Yan et al., 2025). Research highlights ethical issues surrounding data privacy and governance, especially in relation to sensitive data employed for predictive analytics. In higher education and teacher training, these concerns influence the evaluations of student teachers, which are shaped by algorithmic processes (Sajja et al., 2025; Gulson et al., 2022; Williamson et al., 2020). Inadequate regulatory frameworks frequently favour platform providers over educators, thereby necessitating the establishment of ethical AI governance (Hillman, 2023; Nwaimo et al., 2023). Despite the growing focus on AI ethics, a significant portion of the literature remains policy-oriented, lacking insights into practice-based contexts such as Work Integrated Learning (WIL). This study centres on the concerns of rural educators and student teachers regarding data privacy and surveillance in their engagement with AI-supported WIL.

2.2.3 Algorithmic bias and cultural/contextual (mis)fit

AI models are frequently trained on datasets that predominantly reflect an urban, Global North context (Dhiman et al., 2025). In the absence of appropriate adaptation, these models can misinterpret local signals, thereby reinforcing existing power dynamics and perpetuating epistemic injustice (Zhu et al., 2025). Scholars have argued that such models normalise prevailing instructional practices while marginalising alternative approaches (Bulathwela et al., 2024; Zembylas, 2023). Within the realm of teacher education, biased algorithms may distort the interpretation of classroom practices and evaluate competencies inaccurately (Baker & Hawn, 2022; Bull, 2025). Empirical studies indicate that algorithmic systems tend to prioritise efficiency at the expense of critical contextual factors, such as class size and language diversity in rural educational settings (Frempong et al., 2020; Gulson et al., 2022). As a result, AI tools risk reinforcing dominant pedagogical norms and rendering local practices invisible.

2.2.4 Human–AI balance and pedagogical integrity are crucial considerations

The ethical imperative of relational mentoring, professional judgement, and reflective practice is crucial for effective professional learning, which relies on dialogic reflection and the trust established between mentor and mentee—elements that artificial intelligence cannot replicate (Bagai & Mane, 2024). AI should serve to augment, rather than replace, these human dimensions (Raisch & Krakowski, 2021). Key challenges include the development of adaptable AI solutions tailored to local contexts, the establishment of robust data governance frameworks, and the creation of mentorship models that synergise human guidance with AI tools (Umar et al., 2021). While AI has the potential to enhance educational efficiency, uncritical implementation may undermine pedagogical integrity within relational frameworks such as WIL (Mulenga & Shilongo, 2025). Professional learning, which is fundamentally rooted in trust and empathy, cannot be supplanted by automated systems (Holmes & Littlejohn, 2024; Littlejohn & Pammer-Schindler, 2022). An over-reliance on AI may shift the educational focus towards measurement, thereby jeopardising reflective practice and professional agency (Bulut et al., 2024).

3. Theoretical Framework

This study employs Freire's Critical Pedagogy, which conceptualises education as a political act shaped by power relations and agency (Freire, 1970). It examines how AI-supported work-integrated learning (WIL) may either reinforce or challenge existing inequalities within rural teacher education (Mnguni, 2025). The framework underscores the importance of digital access, participation, voice, and humanisation in the experiences of participants engaging with AI mentorship (Rane et al., 2025). Rather than perceiving AI as a neutral entity, this study investigates who benefits from its implementation, who is marginalised, and whose knowledge informs technological development (Bulathwela et al., 2024; Omodan & Marongwe, 2024). This perspective critically addresses the tensions between automation and mentorship, ethical data utilisation, and the necessity for contextually relevant AI practices, thereby enhancing the study's alignment with social justice objectives in rural WIL.

4. Methodology

This study was conducted within an interpretivist research paradigm, which emphasises understanding social phenomena through participants' subjective meanings and lived experiences. An interpretivist perspective was particularly appropriate when the objective of the research was to explore how individuals construct meaning from complex social practices within specific contexts, rather than merely measuring variables or testing causal relationships (Poth & Searle, 2021). The interpretivist paradigm provided a robust foundation for examining how educators and student teachers perceive, experience, and navigate the integration of Artificial

Intelligence (AI) within Work-Integrated Learning (WIL) in rural settings, where contextual factors intricately influence professional learning.

Guided by this paradigm, the study employed a qualitative research approach to generate rich, descriptive, and context-sensitive data that capture the complexity of mentorship, professional development, and the ethical concerns associated with AI-supported WIL. Qualitative inquiry is particularly well-suited to research seeking a deep understanding while closely attending to participants' voices and social realities (Creswell & Poth, 2016; King et al., 2021). Consistent with the study's theoretical foundation in Critical Pedagogy, knowledge was treated as a socially constructed and co-produced phenomenon, emerging from dialogue between the researcher and participants. The dialogue was shaped by considerations of power, voice, and agency (Freire, 1970; Wang, 2026).

The study utilised a qualitative case study design to explore the integration of AI into WIL within a rural teacher education context. A qualitative case study design was particularly appropriate for investigating contemporary phenomena in their real-life settings, especially when the boundaries between the phenomenon and its context are not clearly delineated (Robson, 2024; Yin, 2018). This approach enabled the researcher to capture participants' contextualised experiences, perceptions, and interpretations of AI-supported mentorship and professional development during WIL placements. The investigation centres on the Faculty of Education at a rural university in the Eastern Cape Province of South Africa, with a specific focus on its WIL programme and the increasing utilisation of AI-supported tools during teaching practice placements.

The study focused on the academic staff and student teachers engaged in WIL within the Faculty of Education at a rural university in South Africa's Eastern Cape Province. The population included academic leaders responsible for coordinating WIL, teaching practice supervisors who mentor and evaluate student teachers during their school placements, and student teachers involved in WIL in rural school settings. This group was deemed suitable for the study because its members were directly engaged in the design, implementation, and experiential aspects of WIL, particularly the emerging use of AI-supported tools for mentorship and professional development. A total of 30 participants were purposefully selected from the population to participate in the study (Creswell & Poth, 2016; Yin, 2018). This group comprised six Heads of Department, six teaching practice supervisors, and eighteen student teachers, organised into six focus groups of three participants each.

Data were generated through semi-structured individual interviews and focus group discussions, selected for their effectiveness in eliciting in-depth, experience-based accounts of professional practice in complex contexts. Semi-structured interviews were conducted with Heads of Department and teaching practice supervisors to gather strategic, supervisory, and policy-related perspectives on WIL and the use of AI. This method was chosen for its ability to guide discussions around predetermined topics while allowing the researcher the flexibility to probe participants' responses and explore emerging issues pertinent to mentorship, equity, and ethical considerations (Creswell & Poth, 2016; Yin, 2018). Interviews were held either face-to-face or online, depending on participants' availability and connectivity, with each session lasting approximately 45 to 60 minutes. Focus group discussions were conducted with student teachers to foster collective reflection on their shared experiences of AI-supported WIL during rural school placements. The focus groups were designed to promote interaction among participants, enabling them to elaborate on one another's experiences and highlight common challenges and areas of agreement (Cohen et al., 2018). A total of six focus groups were conducted, each comprising three participants, ensuring that everyone had ample opportunity to contribute to the discussions.

Data were analysed thematically using Braun and Clarke's six-phase approach, which aids in identifying patterns in the dataset (Braun & Clarke, 2021). Audio-recorded interviews and focus group discussions were transcribed and reviewed. Preliminary insights into mentorship, access, ethics, and challenges in AI-supported WIL were recorded. In the second phase, transcripts were inductively coded, labelling segments relevant to the research questions while remaining sensitive to participants' language (Creswell & Poth, 2017). Related codes were clustered into candidate themes in the third and fourth phases, with comparisons made among data from Heads of Department, supervisors, and student teachers to identify similarities and differences in their experiences of AI-supported WIL. The fifth phase defined and named themes to capture their analytical essence, yielding two overarching themes and subthemes aligned with the research questions. Finally, themes were interpreted through a critical pedagogical lens, emphasising power, equity, human agency, and context in AI-supported professional learning (Braun & Clarke, 2021; Freire, 1970).

4.1 Ethical considerations

Ethical approval for the study was obtained from the university's Research Ethics Committee, in accordance with relevant guidelines. Participants were provided with comprehensive information regarding the voluntary nature of the study and their right to withdraw. Written informed consent was secured prior to the commencement of interviews and focus groups. Confidentiality was upheld by assigning codes to participants, and no identifying information was included in the manuscript (Creswell & Poth, 2016; Yin, 2018). The themes were analysed through a critical pedagogical lens, addressing issues of power, equity, and context in AI-supported professional learning (Braun & Clarke, 2021; Freire, 1970). The study included 30 participants: six Heads of Department (HODs), six teaching practice Supervisors (SUPs), and eighteen student teachers, organised into six focus groups. Data were securely stored in password-protected files, and recordings and transcripts were managed in accordance with ethical principles (Creswell & Poth, 2017).

5. Findings and Discussion

Table 1 below demonstrates that the study comprised a total of 30 participants, divided into three distinct groups: six Heads of Departments (HODs), consisting of four males and two females; six Teaching Practice Supervisors (SUPs), comprising five females and one male; and eighteen student teachers organised into six focus groups, with three members in each group, ensuring an equal representation of genders (three males and three females). Data management adhered to ethical guidelines, thereby ensuring the security of audio recordings and transcripts.

Table 1: The biographic data

Participants	**Gender**	**Participant Pseudonyms**
Heads of Department (HODs),	4 Males 2 Female	HOD1, HOD2, HOD3, HOD4, HOD5, HOD6
Teaching practice Supervisors (SUP	5 Females 1 Male	SUP1, SUP2, SUP3, SUP4, SUP5, SUP6
Focus Groups (FGs).	3 Females 3 Males	FG1, FG2, FG3, FG4, FG5, FG6

5.1 Theme 1: AI-supported WIL as a pathway to enhanced mentorship and professional development

This theme explores the application of Artificial Intelligence (AI) in Work-Integrated Learning (WIL) to enhance access to mentorship and professional development in rural teacher education settings. Drawing on participants' experiences, the theme illustrates how AI-supported tools improve mentorship, support reflective practice, and address geographical and resource-related challenges. The sub-themes in this category demonstrate that, when integrated with human-centred mentorship practices, AI promotes more inclusive and sustained professional learning opportunities.

5.1.1 Sub-theme 1.1: Digital access and infrastructural enablement

The study highlights the crucial impact of digital access and infrastructure on rural educators and student teachers engaged in AI-supported Work-Integrated Learning (WIL). Analysis of participant transcripts shows that inadequate connectivity, unreliable electricity, and limited access to digital devices consistently hinder the effective use of AI-driven mentorship and feedback systems. While Heads of Department noted overarching infrastructural challenges, supervisors observed disruptions in mentoring, including delayed feedback and reduced interaction. Student teachers expressed feelings of exclusion and marginalisation due to these limitations, indicating that digital infrastructure is both a technical necessity and a structural determinant of participation in WIL. The findings suggest that existing infrastructural inequities exacerbate rural-urban divides rather than providing equal benefits through technology. Consequently, institutional leadership emphasised the need for robust infrastructure as essential for successful AI integration.

Participant HOD1: "*AI tools function effectively only when connectivity is stable, yet many of our rural schools face frequent network disruptions*".
Participant HOD4: "*Without reliable internet access, using AI consistently during teaching practice becomes challenging*".
Highlighting how infrastructural limitations undermine implementation efforts, supervisors described the tangible ways infrastructural challenges affected mentorship practices.
Participant SUP3: "Sometimes lesson videos and reflections cannot be uploaded on time, which delays feedback and support".
Participant SUP6: "We often rely on alternative methods because the digital platforms fail when connectivity is poor".
Findings on how infrastructural inconsistencies disrupt the continuity of AI-supported mentorship.
Participant FG2: "Our schools do not have Wi-Fi, so accessing AI feedback often requires travelling to town".
Participant FG5: "Data costs and electricity outages make it challenging to engage regularly with the AI tools provided".

The findings underscore that digital access and infrastructural capacity are vital for the effectiveness of AI-supported WIL in rural areas. Participants encountered challenges such as unstable connectivity, limited devices, high data costs, and unreliable electricity, which hindered their engagement with AI feedback and mentorship tools. This observation aligns with existing literature, suggesting that the advantages of AI in education are unevenly distributed and contingent upon infrastructural readiness (Li, 2023; Dyantyi & Mkabile-Masebe, 2025). Furthermore, research in rural teacher education cautions that digital innovations frequently neglect rural realities, thereby reinforcing exclusion rather than promoting equitable professional learning (Langeveldt & Pietersen, 2024; Mncube et al., 2024).

From a Critical Pedagogy perspective, these findings illustrate how material conditions serve as mechanisms of power that influence participation in professional learning. Freire (1970) asserts that educational inequality emerges when learners lack the requisite material conditions for engagement. This study reveals that inadequate digital infrastructure marginalises rural educators and student teachers, constraining their access to AI tools and diminishing opportunities for reflective dialogue. Consequently, enhancing digital infrastructure is a social justice imperative; it is essential for fostering equitable educational practices in AI-supported WIL.

5.1.2 Sub-theme 1.2: AI-Enabled Feedback and Reflective Professional Learning

This sub-theme highlights how AI-enabled feedback mechanisms within Work-Integrated Learning (WIL) enhance reflective professional learning, particularly by improving the reach, timeliness, and consistency of mentorship in rural teacher education contexts. Participants at institutional, supervisory, and student levels reported that AI-supported feedback complements traditional supervision, especially when physical visits are limited. When integrated into human-centred mentorship practices, AI tools were viewed as instrumental in fostering self-reflection, professional growth, and sustained engagement with teaching practices.

From a supervisory perspective, AI is seen as a tool that improves the quality and continuity of feedback.

One participant remarked, Participant SUP2: "*AI assists us in tracking student teachers' progress over time and helps identify areas needing attention prior to formal visits*".
Another supervisor observed,
Participant SUP6: "*The automated feedback serves as a foundation for our discussions and makes our mentoring sessions more focused*".
These insights suggest that AI-enabled feedback fosters reflective dialogue rather than replacing human judgment.
One participant noted,
Participant HOD3: "*AI feedback tools enable us to provide guidance to student teachers even when our supervision capacity is stretched*".
Another institutional leader emphasised that
Participant HOD5: "*The availability of continuous feedback encourages student teachers to reflect on their practice more consistently, rather than waiting for end-of-term evaluations*".
One participant noted,
Participant FG1: "*The feedback we receive through the system encourages us to think critically about our lessons prior to meeting with our supervisors*".
Participant FG4: "*AI-generated comments prompt us to reflect on our teaching and to formulate better questions during mentorship sessions".*

Participants acknowledged that while AI feedbackis insufficient on its own, it significantly enhances engagement with supervisors and improves the timeliness of mentorship, particularly in rural areas. It facilitates reflective practice between meetings, thereby preparing participants for discussions (Hwang et al., 2020; Brandão et al., 2024; Garzón et al., 2025). Effective AI feedback is integrated into human-centred mentoring frameworks, necessitating human interpretation to preserve its pedagogical value (Billett, 2025; Preiksaitis & Rose, 2023). Although it is regarded as a catalyst for reflection, it should not supplant relational supervision. In alignment with Freire's emphasis on dialogue in transformative learning (1970), AI feedback promotes reflective practice and professional agency. Nonetheless, there is resistance to AI that evaluates without fostering dialogue. Thus, AI feedback enhances reflective learning in WIL when it supports dialogic mentorship practices that respect educators' agency and contextual understanding.

5.2 Theme 2: Conditions shaping the implementation and use of AI-supported work-integrated learning

This theme investigates the structural, ethical, and contextual conditions that influence the implementation and utilisation of Artificial Intelligence (AI) in Work-Integrated Learning (WIL) within rural teacher education settings. Drawing on participants' insights, this theme highlights the impact of factors such as infrastructure, data governance, human–AI relationships, and contextual relevance on the effectiveness and equity of AI-supported WIL. Collectively, the sub-themes demonstrate that the successful integration of AI is contingent not only upon technological availability but also upon alignment with pedagogical, ethical, and contextual considerations.

5.2.1 Sub-theme 2.1: Data ethics, privacy, and algorithmic bias

This sub-theme investigates the ethical considerations surrounding data privacy, ownership, and algorithmic bias within the context of AI-supported WIL. Analysis of participant transcripts indicates a prevailing uncertainty regarding data collection and reuse, with Heads of Department articulating concerns related to algorithmic transparency and accountability. Supervisors highlighted the potential risks associated with surveillance, while student teachers expressed anxiety regarding the utilisation of AI feedback tools. These findings suggest that ethical ambiguity may compromise the fundamental pedagogical safety required for reflection and professional development, as AI systems have the potential to perpetuate existing power imbalances. Additionally, institutional apprehensions related to data ownership and governance were also identified.

Participant HOD6: "*We cannot always ascertain where the data goes after lesson videos and feedback are uploaded, which raises accountability issues at an institutional level*".

Participant HOD2: "*AI systems make decisions based on data that we do not fully control, creating challenges when those decisions influence the professional development of student teachers*".

These perspectives highlight apprehension about the systemic consequences of opaque algorithmic processes in teacher education. Supervisors echoed these concerns from the perspectives of mentorship and assessment.

SUP5: "*AI feedback can feel more like surveillance than support when there is a lack of transparency about how judgments are made*"

Participant SUP1: "*Without understanding how the algorithm operates, it becomes challenging to trust that the feedback is fair or contextually appropriate for our students".*

These insights suggest that uncertainty about the logic of algorithms undermines confidence in AI-supported evaluative processes.

Some participants articulated the ethical implications of these practices from an experiential perspective.

One participant noted,

Participant FG3: "*Sometimes we hesitate to be honest in our reflections because we're unsure who might access that information later*".

Participant FG5: "*AI feedback makes you cautious, as it feels like your performance is constantly being evaluated by a system you don't fully understand*".

The study examines the effects of ethical ambiguity on engagement in AI-supported Work-Integrated Learning (WIL). Concerns regarding data privacy, ownership, and algorithmic bias significantly influence participants' trust and engagement, reflecting ongoing discussions about the accountability of educational AI systems (Floridi & Cowls, 2022; Nguyen et al., 2023). In rural areas, the absence of regulatory frameworks exacerbates mistrust and limits engagement with AI feedback. Research indicates that algorithmic systems frequently reflect dominant norms from wealthier educational contexts, resulting in biased evaluations that overlook local pedagogical realities (Joyce et al., 2021; Zhu et al., 2025). This bias may perpetuate inequalities by privileging standardised assessments over context-specific teaching practices (Sambasivan et al., 2021). From a Critical Pedagogy perspective, these ethical tensions underscore power imbalances in AI-supported education. Freire (1970) cautions that education can become dehumanising if learners are unable to challenge the systems that influence them. Concerns regarding surveillance may inhibit essential reflection and dialogue necessary for transformative learning. Freire emphasises the necessity for ethical governance in AI-supported WIL to foster trust and equitable professional development.

5.2.2 Sub-theme 2.2: Balancing human mentorship and AI automation

Participants across all groups consistently acknowledged that while AI can enhance efficiency and provide structured feedback, it cannot substitute for the dialogic, empathetic, and context-sensitive elements of human mentorship. The findings indicate that the value of AI-supported WIL is determined by how automation is integrated alongside, rather than replacing, human engagement.

From a supervisory perspective, participants emphasised that professional learning depends heavily on relational interaction.

Some participants uttered,

SUP6: "*AI can highlight what went wrong in a lesson, but it cannot comprehend the emotional challenges a student teacher encounters in a rural classroom*".

SUP2: "*Automated feedback is helpful, but without discussion, it remains superficial and does not facilitate the professional growth of student teachers*".

These perspectives raise concerns that relying solely on automation falls short of supporting reflective and developmental mentorship. Student teachers echoed these sentiments, emphasising the crucial role of human interaction in interpreting AI-generated feedback.

One participant noted,

FG1: "*AI comments indicate what needs improvement, but they do not clarify why in a manner that connects to your teaching context*".

Another participant remarked,

FG4: "R*eal learning occurs when a supervisor engages in dialogue about the feedback and helps you reflect on your practice*"

These insights demonstrate that AI-enabled feedback is most effective when mediated through human dialogue. Institutional leaders have expressed caution about over-reliance on automation.

One participant reported that:

HOD3: "*Mentorship is fundamentally a human process, and if AI begins to supplant that relationship, we risk undermining the essence of teacher development*".

HOD1: "*AI should assist supervisors by organising information, but it must never replace professional judgement and personal guidance*".

The findings indicate a growing awareness among educational institutions regarding the risks associated with excessive automation in pedagogy. Participants assert that AI should function as a supportive tool rather than an authoritative mentor, emphasising the necessity of balancing AI and human mentorship in Work Integrated Learning (WIL). While AI enhances efficiency and provides valuable feedback, it cannot supplant the relational qualities essential for effective mentorship. Educators underscore the significance of dialogue, empathy, and contextual understanding. Research indicates that AI can enhance formative feedback, particularly when supervisory capacity is constrained; however, there is a risk of reducing professional learning to mere metrics, thereby jeopardising reflective depth and identity development (Bratton et al., 2021; Preiksaitis & Rose, 2023). Freire (1970) posits that education becomes dehumanising in the absence of dialogue, which aligns with participants' resistance to automated mentorship. This study found that AI feedback fostered reflection only when it was integrated with human dialogue, highlighting the importance of human mentorship in situations where emotional support is critical. AI should augment rather than replace human mentorship, ensuring that WIL remains a human-centred space for equitable and transformative learning (Hwang et al., 2020; Brandão et al., 2024; Billett, 2025).

5.2.3 Theme 2.3: Contextual Adaptation and local relevance

This sub-theme examines how the effectiveness of AI-supported WIL is influenced by the extent to which AI tools are customised to the material, cultural, and pedagogical realities of rural school contexts. Across all groups, participants emphasised that when AI systems are designed with assumptions rooted in well-resourced or urban environments, their relevance and pedagogical value in rural settings are significantly constrained. The findings indicate that this contextual misalignment impacts both the usability of AI tools and educators' willingness to engage meaningfully with AI-supported mentorship.

From an institutional perspective, Heads of Department have expressed concerns regarding the limitations of many AI platforms in recognising the challenges faced by rural schools.

One participant reported that: HOD5: "*Most AI systems presume that schools are adequately resourced, which is not the case in rural contexts*".

HOD2"*The recommendations produced by these systems often overlook issues such as overcrowded classrooms and a lack of teaching materials*".

These insights highlight that contextual adaptation is a critical consideration for institutions seeking to implement AI-supported Work-Integrated Learning (WIL) equitably.

Supervisors reinforced these concerns through their interactions with student teachers during placements.

One participant stated,

SUP3: "*AI feedback can be frustrating when it proposes strategies that simply cannot be implemented in rural classrooms*".
SUP6: "*The system does not always consider the improvisation necessary in schools where resources are limited*".
These accounts suggest that discrepancies between algorithmic recommendations and classroom realities may diminish professional confidence rather than foster reflective growth.
One participant noted,
FG4: "*AI suggests tools that are not accessible in our schools, which renders the feedback irrelevant*" (FG4).
Another student teacher remarked,
FG6: "*At times, it seems like the system doesn't grasp the needs of our learners or our community*" (FG6).

Throughout focus groups, students highlighted the necessity for AI tools that adapt to their local teaching contexts rather than impose generic expectations. The findings reveal that the effectiveness of AI-supported Work-Integrated Learning (WIL) in rural areas is influenced by the contextual assumptions embedded in AI systems. Participants noted that these tools often reflect urban pedagogical norms, resulting in misaligned feedback for rural schools. This observation aligns with the literature, which indicates that many educational AI systems fail to account for conditions in under-resourced contexts, thereby limiting their effectiveness (Li, 2023; Joyce et al., 2021; Zhu et al., 2025). Additionally, studies suggest that AI tools that disregard constraints, such as overcrowded classrooms, can marginalise local practices (Sambasivan et al., 2021; Wu, 2024).

From a Critical Pedagogy perspective, these findings demonstrate that decontextualised educational technologies can perpetuate cultural domination. Freire (1970) cautions that the imposition of knowledge systems without contextual relevance leads to oppression, termed cultural invasion. Participants indicated that algorithmic recommendations disconnected from rural realities undermine local knowledge and teaching methods, thereby threatening Freire's principle of humanisation. For AI to effectively contribute to equitable WIL, its design must incorporate context-responsive strategies that engage rural educators and student teachers as co-constructors of knowledge. Without this adaptation, AI risks reinforcing educational inequalities rather than promoting professional learning in rural teacher education.

6. Conclusion

This study examined the potential of AI to enhance Work-Integrated Learning (WIL) in order to support equitable mentorship and professional development within the context of rural teacher education, while also addressing associated challenges and ethical considerations. The findings indicated that AI-supported WIL improved access to mentorship and professional development by expanding networks and enhancing feedback, particularly in isolated rural areas. However, these advantages were contingent upon effective human-centred mentorship, reinforcing the notion that AI should act as a supportive resource rather than a substitute for relational supervision. The study further highlighted constraints in the implementation of AI-supported WIL, including infrastructural inequities, data privacy concerns, and the limited local responsiveness of AI systems. In the absence of reliable digital infrastructure and ethical governance, AI posed a risk of exacerbating existing inequalities in rural education. Through the lens of Critical Pedagogy, the research underscored that AI in WIL is not neutral but is influenced by prevailing power dynamics. For AI to effectively promote equitable professional development, its integration must be guided by principles of humanisation and contextual relevance. This necessitates investment in rural infrastructure, transparent data governance, and hybrid mentorship models that prioritise human relationships. Ultimately, the research contributed to ongoing discussions surrounding AI in teacher education by emphasising the critical need for social justice in innovation.

7. Recommendations

Based on the findings of this study, it is recommended that higher education institutions, policymakers, and educational stakeholders adopt a coordinated, human-centred approach to integrating AI into WIL in rural settings. A primary focus should be on strengthening digital infrastructure in rural schools and universities, ensuring reliable internet connectivity and access to suitable digital devices. Equitable participation in AI-supported WIL fundamentally depends on these essential conditions. Additionally, institutions should develop and implement clear, context-sensitive ethical frameworks that address data privacy, ownership, and the responsible use of AI. This will help build trust and safeguard the professional autonomy of educators and student teachers. Furthermore, AI tools should be integrated into hybrid mentorship models that preserve relational, dialogic supervision, utilising technology to enhance feedback and coordination rather than replace human interaction. It is crucial to actively involve rural educators, supervisors, and student teachers in the design and adaptation of AI-supported platforms to ensure they are contextually relevant and aligned with local pedagogical realities. Finally, sustained capacity-building initiatives should be implemented to enhance digital and AI literacy among all participants, fostering critical, ethical, and reflective engagement with emerging technologies in WIL.

8. Declarations

The authors utilised Microsoft Copilot, a GPT-based language assistance tool, exclusively to enhance the quality of language. This encompassed tasks such as grammatical correction, sentence-level refinement, and enhancements in clarity and readability of the English text. Notably, the AI tool was not employed for any aspect of content generation, data analysis, theoretical development, result interpretation, or decision-making. The authors assert full responsibility for the academic integrity of all content presented in this manuscript, including study design, methodology, data collection, analyses, and resultant conclusions. All revisions facilitated by the AI were meticulously reviewed and overseen by the authors to ensure the highest standards of scholarly rigour.

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CHAPTER TEN

Towards AI-Enhanced Work-Integrated Learning in ICT Programmes in Resource-Constrained Higher Education Contexts: An Autoethnography of Educator Experiences

Refiloe Khitsane
IYunivesithi Walter Sisulu, East London, South Africa
Andiswa Ndaliso-Roji
IYunivesithi Walter Sisulu, Butterworth, South Africa
Matipa Ricky Ngandu
IYunivesithi Walter Sisulu, East London, South Africa
Prince Daughin Ngqabutho Ncube
IYunivesithi Walter Sisulu, East London, South Africa
Gardner Mwansa
IYunivesithi Walter Sisulu, East London, South Africa
Godwin Pedzisai Dzvapatsva
University of Suffolk, Ipswich, Suffolk, England
Courage Matobobo
IYunivesithi Walter Sisulu, East London, South Africa
Corresponding author: Matipa Ricky Ngandu (rngandu@wsu.ac.za)

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Abstract: Work-Integrated Learning (WIL) plays a pivotal role in equipping graduates for professional practice; however, its integration varies in resource-constrained higher education settings, particularly in Information and Communication Technology (ICT) programmes. In such environments, limited availability of industry placements has led to an increased reliance on project-based learning, constituting 60 credits out of a total of 360 programme credits (16.7% of the qualification). Artificial Intelligence (AI) has emerged as a potential tool to enhance WIL through virtual simulations, adaptive feedback, and scalable learning support. Despite its potential, limited attention has been given to how educators engage with and navigate AI-enhanced WIL in disadvantaged contexts. This research adopts a qualitative approach, using a collaborative autoethnographic design involving five ICT lecturers and two WIL coordinators. Data were gathered through structured reflective questionnaires and a facilitated collaborative workshop, and analysed using a hybrid thematic approach that combines inductive and deductive coding informed by socio-technical systems theory. The outcomes reveal five interconnected themes: ambivalent emotional responses, reconceptualisation of pedagogy, a workload paradox, systemic constraints, and context-sensitive strategies for ethical and inclusive AI integration. These results underscore the interaction between social and technical elements and place educators as key figures in navigating AI-enhanced WIL. This study contributes to the academic discourse on AI in higher education by emphasising educator experiences and advocating for contextually grounded and ethically informed practices. It enhances comprehension of how socio-technical conditions influence ethical and inclusive digital advancements in higher education and aligns with UN SDG #4 (Quality Education) and Goal #9 (Industry, Innovation, and Infrastructure).

Keywords: Artificial intelligence, equitable, harnessing, professional development, reimagining.

1. Introduction

Employers expect higher education institutions (HEIs) to produce graduates who possess strong theoretical knowledge and the ability to apply that knowledge in professional contexts immediately (Cook, 2022; Ramnund-Mansingh & Reddy, 2021). Work-Integrated Learning (WIL) supports this aim by combining academic learning with authentic or simulated workplace experiences, thereby enhancing work readiness and employability (Ibrahim & Jaaffar, 2017; Lubbe & Svensson, 2024; Ohei & Brink, 2019; Winberg et al., 2011). WIL is recognised as a critical component of many discipline programmes, including Information and Communication Technology (ICT), as it fosters professional competence, reflective capability, and employability outcomes (Winberg et al., 2011). In ICT programmes, WIL is particularly vital for developing applied problem-solving skills, professional competence, and industry-relevant capabilities.

However, students frequently struggle to appreciate the value of disciplinary knowledge and often find it challenging to transfer what they learn in the classroom to workplace settings (Jackson et al., 2019). While WIL can help address some of these difficulties, significant complications remain. Firstly, much workplace knowledge is tacit and undocumented, making it difficult to integrate into formal curricula. Secondly, workplace practices often require recontextualisation due to the structural and regulatory demands of university programmes.

Despite its pedagogical benefits, the implementation of WIL remains inconsistent, particularly in resource-constrained contexts where access to industry partnerships, infrastructure, and placement opportunities is limited (Winberg et al., 2022). Students in these environments often find it challenging to apply disciplinary knowledge in professional situations (Jackson et al., 2019), and structural constraints further restrict opportunities for authentic professional engagement. Evidence suggests that institutions located in rural or resource-limited areas often struggle to establish industry partnerships, provide sufficient workplace placements, or maintain adequate technological infrastructure (Atta-Owusu et al., 2021; Figueiredo & Fernandes, 2020). Consequently, many ICT programmes rely heavily on project-based learning as a pragmatic substitute for workplace immersion. While this approach facilitates learning integration, it cannot fully replicate the complexities of professional practice or support the development of a robust professional identity.

Artificial Intelligence (AI) has emerged as a potential mechanism for enhancing work readiness through virtual simulations, adaptive feedback, and automated mentoring systems (Ambrose & Isadore, 2025; Borusu, 2025; Nair, 2025; Pradheep Kumar, 2025). AI-enhanced WIL can expand access through virtual simulations, adaptive feedback, and alternative pathways to workplace learning, thereby supporting scalable and personalised learning experiences (Matos et al., 2025). However, existing research has predominantly focused on student outcomes and technological capabilities, with insufficient attention given to the lived experiences of educators tasked with translating these tools into pedagogically sound and contextually appropriate practices (Gayed, 2025; McBean & McBean, 2025). In this study, the term 'educator' refers to all individuals who teach or provide professional educational services at a higher education institution, specifically lecturers and WIL coordinators.

The existing literature offers inadequate insight into how educators in resource-constrained HEIs navigate and comprehend the shift towards AI-enhanced WIL in ICT programmes. Educators in these contexts must contend with infrastructural limitations, large student cohorts, and institutional pressures for digital transformation (Ajani, 2024), alongside concerns regarding readiness, ethics, and training (Maphalala & Ajani, 2025; Rahiman & Kodikal, 2024; Schmidt et al., 2025). The aim of this study is to examine how educators in resource-constrained HEIs experience and navigate the transition towards AI-enhanced WIL in ICT programmes, with particular emphasis on socio-technical, pedagogical, and contextual factors. The study is guided by the following research questions:

- RQ1: How do ICT educators in resource-constrained higher education contexts experience and adapt to AI-Enhanced Work-Integrated Learning in ICT Programmes?
- RQ2: In what ways do socio-technical factors shape the opportunities and challenges educators in resource-constrained higher education contexts face when integrating AI-enhanced WIL into ICT Programmes?
- RQ3: How does the shift toward AI-enhanced Work-Integrated Learning in ICT programmes contribute to the transformation of educators' professional identities and practices in resource-constrained higher education contexts?
- RQ4: What contextual conditions enable or constrain the ethical and inclusive use of AI for expanding work-integrated learning experiences in ICT programmes offered in resource-constrained higher education contexts?

This study addresses the identified research gap by positioning educators as central socio-technical actors in AI-enhanced WIL, rather than as passive implementers of technological systems. These complexities require a human-centred inquiry informed by socio-technical systems theory, which emphasises the interaction between technological tools and the broader organisational, social, and contextual systems in which they operate. From this perspective, the adoption of AI is not merely a technical shift; it is influenced by institutional cultures, educator agency, infrastructural limitations, and localised forms of digital inequality (Katsamakas et al., 2024). Examining AI-enhanced WIL through a socio-technical lens, therefore, enables a richer understanding of how technological affordances intersect with educator experience in disadvantaged higher education settings.

This chapter proceeds as follows: Section 1.1 presents the background and literature context; Section 1.2 outlines the theoretical framework; Section 2 describes the methodology; Section 3 presents the findings; Section 4 discusses the findings; and Section 5 concludes with recommendations.

1.1 Background

This section reviews literature on WIL in ICT programmes, structural constraints in disadvantaged HEIs, and the emergence of AI-enhanced WIL to contextualise the study.

1.1.1 Purpose of WIL in ICT programmes

WWIL facilitates the development of discipline-specific competencies by allowing students to integrate theoretical knowledge with practical application (Kiruthika et al., 2024). WIL is operationalised through four keywork-directed theoretical learning, problem-based learning, project-based learning, and workplace learning (Winberg et al., 2011).

Work-directed theoretical learning aligns academic content with professional roles, while problem-based learning fosters critical thinking through real-world scenarios. Project-based learning emphasises applied problem-solving and accountability, and workplace learning provides direct exposure to professional environments, thereby supporting experiential and social learning (Ramadhan & Nafisah, 2025; Wang, 2018).

Although these modalities contribute to a holistic educational experience, workplace learning remains challenging to implement in resource-constrained contexts. Limited industry partnerships and inadequate infrastructure restrict access to placements, thereby constraining professional identity development and employability outcomes (Campos-Zamora et al., 2022; Jackson & Dean, 2023). Furthermore, participation in WIL has been shown to enhance authentic learning engagement and support the development of adaptive and collaborative competencies in ICT contexts (Jackson & Dean, 2023).

1.1.2 Structural and systemic barriers in disadvantaged HEIs

Disadvantaged HEIs, particularly in rural areas, face systemic constraints that impede the implementation of WIL. Weak industry linkages reduce placement opportunities (Mayombe, 2022; Skinner et al., 2021), while geographic isolation and inadequate infrastructure limit digital engagement (Soobramoney & Govender, 2025). Large student cohorts and limited supervisory capacity further constrain personalised learning (Dzvapatsva et al., 2026; Winchester-Seeto et al., 2024). These constraints underscore the need for flexible, scalable, and context-sensitive approaches to WIL. Unequal access to digital tools exacerbates inequalities and contributes to disparities in graduate work readiness. These intersecting constraints often limit the effectiveness of traditional WIL models and widen the gap between well-resourced and disadvantaged institutions.

1.1.3 Emergence and potential of AI-enhanced WIL

In response to these structural limitations, AI has garnered significant attention as a mechanism for enhancing WIL. AI-enabled tools, including virtual placements, intelligent tutoring systems, and learning analytics, provide scalable alternatives in contexts where access to physical workplaces is constrained (Cerimagic et al., 2022; Dean et al., 2020). These technologies support personalised learning, simulate professional tasks, and enhance the monitoring of student progress (Adil, 2025; Widodo et al., 2024). Nevertheless, existing research predominantly focuses on student outcomes, with insufficient attention given to implementation in disadvantaged contexts or the role of educators (Samman, 2024). Ethical concerns, such as bias and data privacy, also remain inadequately explored (Cui & Alias, 2024). Consequently, further empirical research is necessary to investigate how AI-enhanced WIL can be implemented in ways that are pedagogically grounded and contextually appropriate.

1.1.4 Why educator perspectives matter

Research on AI in education predominantly emphasises technological capabilities and student outcomes (Amado-Salvatierra et al., 2024; Maphalala & Ajani, 2025). This focus overlooks educators as key agents in the design and implementation of AI-enhanced WIL. Barriers such as limited training, insufficient institutional support, and pedagogical misalignment hinder effective AI integration (Rong et al., 2023; Sales, 2025). These challenges are intensified in resource-constrained contexts. AI-enabled tools, such as simulations and automated tracking systems, can support teaching and programme management (Chigbu & Makapela, 2025; Mnguni et al., 2024). Therefore, understanding educator perspectives is essential for enabling the pedagogically meaningful, contextually appropriate, and ethically grounded implementation of AI-enhanced WIL.

1.2 Theoretical Framework

This study adopts socio-technical systems theory as its guiding theoretical framework. Socio-technical systems theory perceives any organised activity, such as teaching or curriculum implementation, not merely as a technical process but as the interaction between social and technical subsystems within a broader institutional environment. The theory posits that sustainable and effective outcomes can only be achieved when both social (human, cultural, organisational) and technical (tools, infrastructure, digital systems) components are jointly optimised (Baxter & Sommerville, 2011; Bostrom & Heinen, 1977; Taxén, 2019).

Socio-technical systems theory has been applied in higher education to understand complex learning environments involving adaptive technologies, learning analytics, and distributed decision-making. For instance, Simonette et al. (2020) frame learning analytics as a socio-technical environment, wherein meaningful outcomes emerge through the interplay of educators, students, and digital tools. Similarly, Navarro-Bringas et al. (2020) assert that AI-mediated systems in universities must be designed with consideration for both technical architecture and human agency, particularly in contexts of organisational change. Recent studies further conceptualise AI as inherently socio-technical, necessitating alignment between human and technological elements (Riesen, 2025; Salwei & Carayon, 2022).

The relevance of socio-technical systems theory to this study resides in its capacity to conceptualise the implementation of AI-enhanced work-integrated learning (WIL) as more than a technological upgrade. It facilitates an exploration of how educators, as key human actors, navigate, adapt to, and reshape the transition to AI-mediated practices. This aligns closely with the aim of the study, which is to examine how educators in resource-constrained institutions experience and manage the pedagogical, organisational, and contextual dimensions of AI-enhanced WIL in ICT programmes. This framework informed the design of reflective prompts addressing both social and technical dimensions.

Socio-technical systems theory also provides a lens through which to examine the tensions and trade-offs involved in deploying AI in environments characterised by limited infrastructure, evolving digital skills, and uncertain policy contexts. By foregrounding the interaction between social and technical subsystems, the framework enables a more holistic understanding of both the barriers and enablers of equitable and sustainable innovation in WIL. In higher education, AI adoption is increasingly framed as a socio-technical process shaped by pedagogical and organisational factors (Alshahrani et al., 2024; Swist & Gulson, 2023).

2. Methodology

This study adopted a qualitative approach employing a collaborative autoethnographic research design to examine how educators in resource-constrained, rural-based higher education environments experience and negotiate the transition towards AI-enhanced WIL in ICT programmes. This qualitative approach was selected as it facilitates an in-depth exploration of lived experiences and meaning-making processes, which are central to understanding socio-technical transitions in education. Autoethnography was chosen because it allows researchers to critically reflect on their own professional experiences while situating these within broader socio-cultural, organisational, and technological contexts (Herrmann & Adams, 2024). The research design is appropriate as it captures experiential, contextual, and reflexive dimensions that cannot be accessed through quantitative methods.

Collaborative autoethnography was selected as it facilitates multiple educator perspectives and supports collective meaning-making, thereby enhancing the depth, credibility, and resonance of the findings (Chang et al., 2016). The population comprised ICT educators engaged in WIL within rural higher education contexts, with participants purposefully selected based on their direct involvement in WIL delivery, coordination, and AI integration. The collaborative autoethnographic cohort consisted of five ICT lecturers and two WIL coordinators working at a rural university in the Eastern Cape Province of South Africa. Purposive sampling ensured that participants possessed relevant experiential knowledge aligned with the study objectives. As autoethnography positions researchers as both participants and analysts, the sample reflects the population under investigation (Makwembere et al., 2021; Trifan et al., 2024).

2.1 Data collection and sampling

Data were collected using a structured online reflective questionnaire, chosen for its capacity to systematically capture individual experiences while allowing for flexibility in reflective depth. Each educator independently documented their experiences, challenges, and strategies related to AI-enhanced WIL. Participants subsequently shared their reflections, which were collaboratively discussed in a facilitated workshop aimed at identifying patterns and refining interpretations, thereby enhancing the credibility of the findings. The workshop was guided by structured prompts to ensure consistency and analytical focus across contributions. All responses were anonymised using participant codes (WIL01–02; Lect01–05).

2.2 Data analysis

Data analysis was conducted using a hybrid thematic approach that combines inductive and deductive coding (Fereday & Muir-Cochrane, 2006; Proudfoot, 2023). This approach was selected as it facilitates the integration of theory-driven insights from socio-technical systems with emergent, context-specific meanings derived from participants' lived experiences, thereby ensuring both analytical rigour and contextual sensitivity. Phase 1 involved familiarisation through repeated reading; Phase 2 encompassed initial coding; Phase 3 involved clustering into candidate themes; Phase 4 consisted of reviewing themes against the dataset; Phase 5 entailed refining and naming themes; and Phase 6 focused on producing the analytic narrative (Braun & Clarke, 2022). This process enabled systematic interpretation aligned with socio-technical systems theory. Analytical decisions were iteratively discussed among researchers to enhance interpretive rigour.

Ethical clearance was obtained from the departmental ethics committee, and informed consent was secured from all participants. Confidentiality, voluntary participation, and data protection protocols were strictly maintained. Trustworthiness was ensured through credibility (collaborative validation), dependability (transparent procedures), confirmability (audit trail), and reflexivity embedded in autoethnographic practice (Lincoln et al., 1985).

3. Data Presentation and Results

In this section, we present the data and the results from the collaborative autoethnographic strategy rooted in interpretivism philosophy focusing on subjective experiences and personal narratives to build insights from the qualitative data collected.

Table 1: *Participants' profiles*

Participant	Role	Experience
Lect01	Lecturer	More than 10 years
Lect02	Lecturer	More than 10 years
Lect03	Lecturer	More than 10 years
Lect04	Lecturer	7 to 10 years
Lect05	Lecturer	More than 10 years
WIL01	WIL Coordinator	More than 10 years
WIL02	WIL Coordinator	1 to 3 years

As illustrated in Table 1, the participant group comprised five lecturers and two WIL coordinators, thereby reflecting a balance between pedagogical and administrative perspectives pertinent to the implementation of WIL. The majority of participants (five out of seven) reported over ten years of professional experience, indicating a cohort characterised by considerable experience and substantial institutional knowledge. One lecturer indicated having between seven and ten years of experience, while one WIL coordinator reported having between one and three years of experience, thus providing a relatively early-career perspective.

The analysis employed a hybrid inductive–deductive thematic approach informed by socio-technical systems theory. This method ensured that the findings remained firmly grounded in the lived experiences of the participants while simultaneously facilitating a theoretically informed interpretation.

The thematic analysis resulted in five interrelated themes that encapsulate participants' emotional, pedagogical, cognitive, and structural experiences related to the integration of artificial intelligence into WIL. Each theme is presented alongside supporting interpretations and illustrative results. As delineated in Table 2, the following themes were identified:

- Ambivalent perception and emotion- this theme aligns with the first research question [RQ1] focusing on how educators experience and adapt to AI.
- Reconceptualising pedagogy- this theme aligns with the second theme [RQ3], examining the ways socio-technical factors shape integration.
- Workload paradox- this theme responds to the fourth research question [RQ4] exploring the transformation of educators' professional identities and practices.
- Systemic constraints- this theme extends from the workload paradox and directly responds to the fourth research question [RQ4], which focuses on contextual conditions on educators' abilities to use the new technologies effectively.
- Strategies for integration- this theme provides insights into the second research question [RQ2], which focuses on examining the ways socio-technical factors shape integration.

Table 2: *Codes and themes*

Themes	Codes
Ambivalent perception and	Mixed emotions; Cautious optimism; Apprehension

emotion	about trust and ethics; Evolution from scepticism to adoption; Sense of relief from reduced burden
Reconceptualising pedagogy in the presence of AI	Shift from product to process; Focus on critical skills over content; Concern over academic integrity
Workload paradox of AI adoption	Reduced administrative load; Increased cognitive load for verification; New supervisory demands
Systemic and structural constraints to AI integration	Technological access and connectivity barriers; Absence of institutional policy; Inadequate training and support
Context-sensitive strategies for ethical and inclusive AI integration	Scaffolding and guided use; Advocacy for policy and equity; Use of low-cost and open-source tools

3.1 Ambivalent perception and emotion

Participants expressed ambivalent emotional responses towards AI adoption, characterised by a tension between optimism and caution. While AI was perceived as a promising tool with the potential to enhance efficiency and support teaching practices, this optimism was tempered by concerns regarding trust, ethical use, and data integrity. Several participants described experiencing mixed emotions, particularly in relation to the reliability of AI-generated outputs:

I experience mixed emotions when working with or when I consider working with AI-mediated tools. I anticipate, with some caution, good and relevant contributions from AI tools. This positive anticipation also comes with a cloud of cautious optimism because am not sure I can trust the contributions fully. Lect01

As I engaged more deeply with the technology, these feelings evolved into cautious confidence and professional curiosity, informed by a growing recognition of AI's potential to reduce administrative burden and support scalable, efficient learning when used responsibly. Lect04

Others acknowledged feeling encouraged by AI's capabilities while simultaneously remaining apprehensive about errors and privacy risks

… I feel encouraged by AI because it helps reduce workload, but I remain cautious about mistakes and data privacy. WIL02

… I experience a mix of curiosity, cautious optimism, and professional reflection. Lect05

Notably, some participants reported a shift in perception, moving from initial scepticism to a more informed and cautious adoption. As one lecturer explained, early doubts gave way to advocacy for ethical AI use once familiarity and understanding increased:

… I was sceptical about using the tools, but realised the power that these tools have … Now I encourage ethical use of the tools. Lect03

Alongside these concerns, AI also evoked a sense of emotional relief, particularly through the reduction of routine administrative tasks, which participants described as alleviating professional strain.

It raises a sense of relief as it significantly reduces administrative burden and improves accuracy in WIL coordination. WIL01

Participants exhibit ambivalent perceptions of AI, characterised by a balance between cautious optimism and underlying concerns regarding reliability and trust. Although many acknowledge the potential of AI to enhance efficiency and alleviate workloads, their acceptance is moderated by a critical awareness of ethical considerations. Overall, this indicates a transitional phase in which trust in AI is still evolving alongside a growing appreciation of its benefits.

3.2 Reconceptualising pedagogy in the presence of AI

AI integration prompted participants to rethink the pedagogical foundations of WIL, moving beyond traditional product-oriented assessments towards a stronger emphasis on learning processes, authenticity, and critical engagement. Rather than focusing on content reproduction, participants reported designing learning activities that prioritise reasoning, reflection, and contextual application.

One participant noted that AI influenced how WIL was designed, delivered, and evaluated, encouraging greater attention to authenticity and critical engagement:

AI has influenced the way I design, deliver, and evaluate WIL by prompting a greater emphasis on authenticity, process, and critical engagement. Lect04

Similarly, another participant highlighted a shift toward assessing higher-order cognitive skills rather than knowledge generation alone:

Now, I create WIL opportunities that test students' critical thinking skills rather than focusing on knowledge generation or content creation. Lect05

However, this pedagogical transformation was accompanied by persistent concerns regarding academic integrity. Participants expressed anxiety about students' unethical use of AI, particularly the uncritical submission of AI-generated content as original work:

… I have concerns about student over-reliance, ethical use, and data privacy. In large classes, monitoring AI use is difficult, and I haven't yet explored its full potential due to time and limited institutional guidance/support. Lect02

… this optimism remains tempered by ongoing ethical vigilance, especially around equity, transparency, and over-reliance on automated outputs, resulting in a balanced emotional stance that combines pragmatism with a strong commitment to human-centred and ethically grounded educational practice. Lect04

… I also feel a degree of concern and responsibility, particularly regarding academic integrity, over-reliance by students, ethical use of data, and the risk of widening existing digital inequalities. Lect05

AI integration is driving a shift in WIL pedagogy from content-focused teaching to process-oriented learning that emphasises authenticity, critical thinking, and higher-order skills. This suggests a transformation in both teaching and assessment practices, with an increased focus on competencies that are less easily replicated by artificial intelligence. However, concerns regarding over-reliance on AI, ethical considerations, and limited institutional support highlight ongoing challenges in the effective implementation of these changes.

3.3 Workload paradox of AI adoption

A central finding of the study is the workload paradox associated with the utilisation of AI. While AI significantly mitigates administrative demands, including report drafting, scheduling, and data organisation, it concurrently escalates cognitive and evaluative workload.

Participants acknowledged that AI automation eased time pressures related to routine tasks:
AI has eased the administrative load by automating tasks like report drafting, data organization and scheduling, allowing me to focus more on meaningful WIL interactions and decision making. WIL02
… there is excitement about AI's potential to enhance efficiency, personalise learning, and reduce administrative burdens, which can allow more time for meaningful student engagement and scholarly work. Lect05
… these feelings evolved into cautious confidence and professional curiosity, informed by a growing recognition of AI's potential to reduce administrative burden and support scalable, efficient learning when used responsibly. Lect04
However, this benefit was offset by the additional cognitive effort required to verify, contextualise, and assess AI-supported student work. One participant observed that reviewing AI-generated outputs required careful scrutiny, thereby increasing mental workload:
AI has reduced my administrative workload and simplified routine tasks, but it also adds cognitive effort in reviewing outputs. Lect02
Furthermore, AI introduced new supervisory demands, compelling lecturers to exercise heightened professional judgement in evaluating the quality, originality, and ethical use of AI-assisted work:
… AI has increased the demand on my professional judgement, as I now need to evaluate the quality, appropriateness, and ethical implications of AI-supported student work, particularly in assessment and supervision contexts. Lect04
The findings reveal a paradox in AI adoption: automation reduces routine administrative tasks while simultaneously increasing lecturers' cognitive and evaluative workload. Throughout the transcripts, participants consistently indicate that the time saved through AI is offset by the need for critical verification, ethical scrutiny, and professional judgement when assessing AI-assisted work. This suggests that AI shifts, rather than eliminates, workload—reallocating effort from administrative efficiency to higher-order cognitive and evaluative responsibilities.

3.4 Systemic and structural constraints to AI integration

Participants consistently identified systemic constraints that hinder meaningful and equitable AI integration within WIL, particularly in rural and under-resourced university contexts. Limited access to reliable internet connectivity and suitable digital devices emerged as a significant barrier constraining both lecturers' and students' ability to engage effectively with AI tools:
Technological constraints include unreliable internet connectivity, limited access to suitable devices, outdated institutional infrastructure, high data costs, and insufficient technical support. These challenges restrict consistent student engagement with AI tools and limit the effective integration of AI into WIL activities at a rural university. Lect05
Limited AI access, lack of policy, minimal training, and weak infrastructure make it hard to scale AI-enhanced WIL. Lect02
Irregular access to technologies and subscription issues. Powerful tools require subscriptions that most of our students cannot afford. Lect03

In addition to infrastructural challenges, participants highlighted the absence of clear institutional policies governing AI use. The lack of formal guidelines made it difficult for lecturers to assess whether their practices aligned with institutional expectations or ethical standards.

In the absence of known policies and procedures, it is difficult to gauge whether what I am doing is in alignment. Lect01

A primary challenge is the absence of clear, consistent institutional policies and guidelines on the acceptable use of AI in teaching, assessment, and supervision. Lect04

Training and support were also described as insufficient. Participants reported minimal formal professional development on AI integration, resulting in heavy reliance on self-directed learning and informal experimentation:

Formal training on AI integration has been limited, especially for non-academic staff. More support is coming through general digital platforms rather than structured institutional programmes. As a result, effective use of AI has largely depended on self-directed learning, highlighting the need for more systematic capacity-building to support sustainable AI integration in WIL. WIL01

The findings show that AI integration is hindered by limited infrastructure, a lack of clear policies, and insufficient training. As a result, adoption is inconsistent and relies on individual effort rather than institutional support.

3.5 Context-sensitive strategies for ethical and inclusive AI integration

Despite systemic challenges, participants demonstrated adaptive and contextually responsive strategies for integrating AI into WIL. A key approach involved scaffolding and guided use, whereby students were first grounded in core concepts before being introduced to AI as a supportive tool rather than a substitute for learning:

I ensure that students have a solid background of concepts first and then use AI for scaffolding. Lect03

Participants also advocated for the development of institutional policies and equitable access, calling for clear guidelines, practical training, and improved infrastructure support. This is supported by:

Develop clear policies, provide practical training, improve access to tools, and use AI to support, not replace, human judgment in WIL. Lect02

In recognition of resource constraints, some participants emphasised the use of low-cost or open-source AI tools to ensure inclusivity and prevent the marginalisation of students who lack access to premium technologies:

Ensure tools are accessible to all students, involve students in planning, protect data, align AI solutions with local industries and cultural context, use low-cost or open-source tools with gradual staff training and small pilot projects, and continuously collect feedback to adapt and improve practices. WIL02

Participants demonstrate context-sensitive AI integration by balancing pedagogical support, ethical considerations, and inclusivity. Their focus on scaffolding, policy development, and equitable access reflects efforts to reduce risks such as exclusion and over-reliance on AI. Overall, effective integration requires alignment with local contexts and institutional support.

4. Discussion of Findings

This section discusses how the findings address the study's four research questions. The five identified themes—ambivalent emotion, reconceptualising pedagogy, workload paradox, systemic constraints, and context-sensitive strategies—reflect the complex interplay between the social and technical dimensions of AI-enhanced WIL. These findings are framed by socio-technical systems theory, which emphasises the importance of optimising both human and technological subsystems in tandem (Navarro-Bringas et al., 2020; Taxén, 2019).

4.1 Ambivalent emotion and educator reflexivity

This theme addresses RQ1 and RQ3 by examining educators' emotional and ethical responses to AI integration.

Participants expressed a mixture of cautious optimism, curiosity, and ethical concern regarding the integration of AI tools. This ambivalence reflects the emotional labour involved in adopting new technologies, a theme also noted in educator-focused AI studies (Gayed, 2025; McBean & McBean, 2025). While educators welcomed the reduction of administrative burdens, they also experienced anxiety about trust, bias, and responsible use—concerns echoed by Rong et al. (2023) and Williams (2025), who critique the overemphasis on AI's technical promise while overlooking its impact on educators' roles and responsibilities.

This theme aligns with Barrett and Pack (2023), who emphasise that the absence of institutional frameworks for AI use in education places the ethical burden on individual educators. In response, educators begin to take on roles not only as instructors but also as ethical stewards of AI integration. This identity shift from knowledge transmitters to ethical facilitators is similarly discussed by Amado-Salvatierra et al. (2024), who argue that AI adoption reshapes educators' responsibilities within socio-technical systems.

4.2 Reconceptualising pedagogy in the presence of AI

This theme addresses RQ1 and RQ3 by highlighting how AI integration has reshaped WIL pedagogy and educator identity.

Findings indicate that AI adoption has prompted a shift in pedagogical design, with educators moving away from content reproduction towards process-oriented learning that emphasises critical thinking, authenticity, and reflection. This aligns with Jackson et al. (2019), who note that students struggle to apply disciplinary knowledge in real-world settings, necessitating pedagogy that fosters contextual reasoning.

Participants' growing concern with academic integrity and equitable access underscores the importance of scaffolding AI use, rather than adopting it as a wholesale substitute for learning.

This concern aligns with Cui and Alias (2024), who highlight the tension between the efficiency benefits of AI and the risks it poses to integrity and inclusivity in higher education. Sales (2025) emphasises the need for ethical guidance and educator preparedness, while Yan et al. (2025) advocate for embedding ethical AI literacy in pedagogical design to support reflective and responsible AI use.

4.3 The porkload paradox of AI adoption

This theme addresses RQ1 and RQ2 by demonstrating how AI improves efficiency while generating new cognitive and supervisory demands within socio-technical systems.

While AI tools have helped reduce repetitive administrative tasks such as scheduling and report drafting (WIL02), this efficiency has been offset by an increased cognitive load due to the need for output verification and ethical judgement, reflecting the workload paradox. This aligns with Maphalala and Ajani (2025), who argue that insufficient training and support structures compel educators to invest additional time in learning and managing AI systems, thereby creating new layers of workload.

This is supported by Katsamakas et al. (2024), who show that in under-resourced institutions, AI integration often imposes new supervisory demands and creates workload pressures in the absence of clear institutional frameworks. Educators in this study reported intensified professional scrutiny in evaluating student work for originality and ethical alignment, signalling that AI may redistribute rather than alleviate work-related pressure.

4.4 Systemic constraints and institutional gaps

This theme addresses RQ2 and RQ4 by identifying barriers to equitable and effective AI integration in resource-constrained higher education.

Systemic and infrastructural barriers, such as limited internet access, a lack of devices, and unclear institutional policies, were consistently reported. These challenges echo earlier findings by Winberg et al. (2022) and Ajani (2024), which outline how rural HEIs face limitations in digital readiness and industry engagement.

This study also reinforces the findings of Mnguni et al. (2024), who discovered that uneven digital infrastructure hinders equitable access to AI-enhanced learning. The absence of formal training and institutional guidance led to a reliance on informal learning, compounding inequality and slowing adoption. This aligns with broader research that highlights gaps in AI literacy, uneven educator preparedness, and the lack of coherent institutional guidance for responsible AI integration in higher education (Cui & Alias, 2024; Mwansa & Ngandu, 2026). Similarly, Jose et al. (2025) warn that abstract ethical policies, when not embedded in institutional structures, leave educators to interpret and enforce ethical boundaries on their own.

4.5 Context-sensitive strategies for ethical and inclusive AI integration

This theme addresses RQ3 and RQ4 by demonstrating how educators adapt their practices to support the ethical, inclusive, and contextually relevant integration of AI.

Despite systemic limitations, educators employed adaptive strategies, including low-cost tools, open-source platforms, and scaffolding techniques. These practices reflect a human-centred, ethically informed pedagogy that aligns with the perspectives of Borusu (2025) and Nair (2025), who advocate for transformative WIL through inclusive AI practices.

Participants emphasised the necessity for institutional policies that reflect local realities and promote equitable access, a sentiment echoed by Chigbu and Makapela (2025), who highlight the importance of aligning AI solutions with community-specific constraints. The emphasis on accessible tools and gradual implementation further supports Gayed's (2025) argument that AI adoption must consider equity, rather than solely efficiency.

4.6 Revisiting socio-technical systems theory in context

This section synthesises the findings through a socio-technical lens, addressing RQ1–RQ4 and highlighting the interdependence of human, technological, and institutional factors in AI-enhanced WIL. The findings extend socio-technical systems theory by demonstrating how misalignments between social and technical subsystems manifest in resource-constrained contexts. Educators' emotional responses, pedagogical adaptations, and evolving identities reflect the social subsystem, whereas limitations in infrastructure, policy, and training constrain the technical and organisational subsystems. Challenges such as increased cognitive workload, ethical uncertainty, and unequal access emerge from weak alignment between these subsystems. Conversely, adaptive strategies, including scaffolded AI use and accessible tools, illustrate how local practices can partially restore balance. Consequently, effective AI integration depends on coordinated institutional support, educator capacity, and context-sensitive implementation.

4.7 Implications for practice

The findings indicate several practical considerations for the implementation of AI-enhanced WIL in resource-constrained higher education contexts. A key priority is the development of clear, contextually grounded institutional frameworks to guide the ethical and pedagogical use of AI. In the absence of such frameworks, decision-making becomes individualised, resulting in inconsistency and uncertainty across programmes. Additionally, there is a need for structured professional development to support educators in the integration of AI within WIL. Such initiatives should combine technical training with pedagogical guidance and ethical awareness, enabling educators to make informed, context-sensitive decisions in practice. Equitable access to digital infrastructure remains a critical enabling condition. Institutions should prioritise reliable connectivity, access to appropriate devices, and the utilisation of accessible or open-source AI tools to mitigate barriers to participation. Pedagogically, AI should be incorporated through guided and scaffolded approaches that position it as a support for learning rather than a substitute for student engagement. This strategy can help maintain academic integrity while promoting critical and reflective learning. Implementation should also be phased, allowing for ongoing evaluation and adaptation. Such an approach supports responsiveness to contextual constraints and reflects the complexity of socio-technical systems in higher education.

5. Conclusions and Recommendations

This chapter examines how educators in resource-constrained, rural-based higher education settings experience and navigate the transition to AI-enhanced WIL in ICT programmes, drawing on qualitative data from a collaborative autoethnographic study. The findings reveal five interconnected themes: ambivalent educator emotions and reflexivity, reconceptualised pedagogy in the presence of AI, the workload paradox of AI adoption, context-sensitive strategies for ethical and inclusive AI integration, and systemic institutional constraints. Collectively, these themes address the research questions presented in Section 1.1.1 and illustrate how educators negotiate professional identity, pedagogy, and socio-technical challenges within AI-integrated WIL environments, highlighting the need for supportive institutional and pedagogical frameworks.

The findings extend the existing literature on AI adoption in resource-constrained higher education, particularly concerning widening digital divides, algorithmic bias, data privacy, and ethical tensions. Grounded in socio-technical theory, this study positions educators as non-passive recipients of AI technologies but as central agents in shaping pedagogical innovation and ethical practice. Strategic integration of AI for WIL can enhance feedback quality, support authentic learning experiences, and facilitate the development of tacit knowledge and practical skills for contemporary workplaces. Although not directly reflected in the empirical data, persistent challenges in securing WIL placements, largely driven by systemic constraints and weak industry partnerships, remain significant. AI-enabled pedagogical approaches may partially alleviate these pressures through simulated, project-based, or work-directed learning alternatives.

Despite the potential benefits identified, the study highlights critical challenges, including inequitable access to digital infrastructure, uneven institutional readiness, and limited opportunities for sustained educator professional development. In resource-constrained contexts, these challenges intensify emotional, pedagogical, and workload pressures, underscoring the risk that AI adoption may exacerbate existing inequalities without adequate institutional support.

This chapter contributes practical insights into how educators can navigate and manage the transition toward AI-enhanced practices across multiple WIL modalities. Methodologically, it demonstrates the value of collaborative autoethnography for capturing reflexive, contextually grounded accounts of AI-enabled pedagogical change.

To extend the implications for practice provided in Section 4.7 regarding institution-wide strategies recommending responsible AI adoption, this chapter advances this direction by focusing on governance, accountability, and sustainability. It recommends context-sensitive policies that foreground ethical alignment and inclusivity, thereby enabling the transformative potential of AI-enhanced work-integrated learning in resource-constrained higher education contexts. Finally, the chapter advocates for the development of a phased professional development programme that includes: (a) foundational AI literacy for all staff, (b) discipline-specific workshops for ICT educators on AI tools relevant to WIL, and (c) ongoing peer-learning communities for knowledge sharing.

A key limitation of the study is its small sample size and short time horizon, as data were collected from seven educators within a single institution, limiting generalisability; however, the participants' extensive professional experience enhances the credibility of the findings. In addition, the rich contextual detail enables readers to assess transferability to similar contexts. Future research should incorporate larger samples and comparative analyses across differently resourced institutions to strengthen generalisability and inform equitable AI-enhanced WIL frameworks.

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CHAPTER ELEVEN

AI-Driven Assessment and Feedback in Work-Integrated Learning: A Systematic Review of Authenticity, Ethics, and Professional Competence

Bunmi Isaiah Omodan
Institute for Open and Distance Learning,
University of South Africa, Pretoria, South Africa

Cias T. Tsotetsi
Academic and Research,
University of the Free State, QwaQwa Campus, South Africa

Corresponding author: bunmiomodan@gmail.com

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Abstract: Artificial intelligence (AI) is rapidly transforming the methods by which higher education institutions assess learning and provide feedback; however, its implications for work-integrated learning (WIL), wherein assessment must accurately reflect authentic professional performance, remain under-theorised. This systematic review synthesises evidence on AI-based assessment, automated feedback, learning analytics, and competency evaluation as they pertain to authenticity, ethics, and professional competence in WIL and related higher education contexts. Following the PRISMA 2020 guidelines, five databases (Scopus, Web of Science, ERIC, EBSCOhost, and the ACM Digital Library) and supplementary citation searching yielded 1,175 records. After the removal of duplicates and a two-stage screening process, 20 studies published between 2017 and 2025 were included and synthesised narratively in relation to four review questions. Findings indicate that AI tools can enhance the efficiency, scalability, and timeliness of feedback and support personalisation, particularly for the reflective and formative writing tasks that are central to WIL. However, the same tools raise persistent concerns: threats to assessment authenticity and academic integrity from generative AI, demonstrable algorithmic bias against linguistically and culturally diverse learners, a lack of transparency that undermines clarity, and the risk of over-automation that displaces the situated human judgement essential for professional competence. The review argues that AI should augment rather than replace evaluative judgement, and that authentic WIL assessment requires human-in-the-loop designs, validity-centred reform, and explicit attention to equity. Implications for assessment design, policy, and future research are discussed.

Keywords: Artificial intelligence, work-integrated learning, authentic assessment, automated feedback, academic integrity, professional competence.

1. Introduction

Assessment occupies a central position in the relationship between higher education and the world of work. Through assessment, institutions ensure that graduates are competent to practise, students learn what is valued, and the curriculum conveys the standards of a profession. Work-integrated learning (WIL), which encompasses a range of pedagogies that connect academic study with authentic experiences of practice through placements, internships, clinical rotations, simulations, and project work, has emerged as a defining characteristic of contemporary higher education, precisely because it promises to align what is learned with what professionals actually do (Billett, 2009; Smith, 2012). However, assessing learning in these contexts is notoriously challenging. It must capture situated, holistic performance under conditions that universities only partially control, and it must do so fairly and at scale (Ajjawi et al., 2020; McNamara, 2013).

Into this already complex landscape has entered a powerful and contested technology. Artificial intelligence (AI) is now being applied throughout the assessment lifecycle: automated essay and short-answer scoring, intelligent tutoring and adaptive testing, learning-analytics dashboards, natural-language feedback on writing and reflection, and, most recently, generative AI systems capable of producing assessable artefacts on demand (González-Calatayud et al., 2021; Luckin, 2017; Swiecki et al., 2022; Zawacki-Richter et al., 2019). Advocates argue that AI can alleviate the marking burden, accelerate feedback, personalise learning, and reveal patterns that are invisible to human markers (Cavalcanti et al., 2021; Holmes et al., 2019). Critics counter that the same systems can encode bias, undermine the validity of assessment, and erode the professional judgement that WIL is intended to foster (Baker & Hawn, 2022; Gardner et al., 2021).

These tensions are most pronounced in WIL. Authentic assessment in WIL relies on context, relationships, and professional discernment, qualities that resist datafication (Ajjawi et al., 2020; Villarroel et al., 2018). When a reflective journal is scored by an algorithm, when a placement competency is inferred from analytics, or when a student can generate a polished portfolio with a chatbot, the meaning of "authenticity" is put under strain (Dawson et al., 2024; Kofinas et al., 2025). Whether AI strengthens or weakens authentic WIL assessment is therefore not a narrow technical question, but rather a question concerning fairness, integrity, and the future of professional formation.

The stakes are amplified by scale. WIL has moved from the margins to the mainstream of higher education, embedded as a graduate-employability strategy across disciplines from health and engineering to business and the creative industries (Billett, 2009; Rowe & Zegwaard, 2017; Smith, 2012). At the same time, AI has diffused through education at a pace that has outstripped institutional governance, with generative tools in particular becoming widely available to students almost overnight (Bond et al., 2024; Crompton & Burke, 2023). The result is a mismatch: a high-volume, high-stakes assessment practice confronting a fast-moving, under-regulated technology. Reviews of the broader field have consistently noted that AI in education has advanced with limited attention to pedagogy, ethics, or the educators tasked with its implementation (Zawacki-Richter et al., 2019). A synthesis that brings these literatures into dialogue with the specific demands of WIL is therefore timely.

Despite a rapidly growing literature on AI in higher education assessment, no synthesis has examined this evidence specifically through the lens of WIL and professional competence. Existing reviews map AI applications broadly (Bond et al., 2024; Crompton & Burke, 2023; Zawacki-Richter et al., 2019) or focus on single functions such as automated feedback (Cavalcanti et al., 2021; Deeva et al., 2021), but they do not foreground the distinctive demands of authentic, work-based assessment. This review addresses that gap. It asks whether, and under what conditions, AI-driven assessment and feedback enhance the efficiency, fairness, and quality of assessment in WIL contexts, and where they introduce risks to authenticity, integrity, equity, and human professional judgement.

The review is guided by four questions: *RQ1: How do AI tools affect the efficiency, scalability, and personalisation of assessment and feedback in WIL and related higher education contexts? RQ2: How do they affect the authenticity of assessment and academic integrity? RQ3: What evidence exists regarding fairness, bias, and transparency? RQ4: How do AI tools relate to professional competence and the exercise of human evaluative judgement?* The remainder of the article sets out the theoretical framing, details a PRISMA-guided method, reports a narrative synthesis of 20 included studies, and discusses implications for the changing relationship between higher education and the workplace.

2. Theoretical Framing

This review is grounded in three theoretical frameworks that collectively elucidate the appeal and potential risks of AI-driven assessment in WIL: theories of authentic assessment, theories of evaluative judgement and feedback, and sociotechnical perspectives on educational technology.

2.1 Authentic assessment and authenticity in WIL

Authentic assessment seeks to mirror the tasks, standards, and conditions of professional practice so that what is assessed resembles what graduates will do (Villarroel et al., 2018). Villarroel and colleagues (2018), synthesising 125 studies, identified three dimensions of authenticity: realism, cognitive challenge, and evaluative judgement. WIL is, in effect, authentic assessment's most demanding case because the "real world" is not simulated but actual, and because performance is observed by both workplace and academic assessors (Bosco & Ferns, 2014; McNamara, 2013). Ajjawi et al. (2020) argue that authenticity in WIL is not singular but plural, contextual, task-based, and personal, meaning that any technology claiming to assess "authentically" must be interrogated for the type of authenticity it preserves and the kind it erodes. This plurality provides an analytic yardstick for the present review: AI tools may enhance task realism while flattening personal and contextual authenticity.

The WIL assessment literature has long wrestled with this complexity independently of AI. McNamara (2013) shows that assessing professional competence in WIL is challenging precisely because competence is holistic and context-bound, exceeding what any single instrument can capture. Bosco and Ferns (2014) argue for embedding authentic tasks directly within the WIL curriculum rather than bolting assessment on afterwards. These accounts establish a baseline expectation against which AI must be judged: an assessment is authentic to the extent that it engages realistic, cognitively demanding tasks and supports students in forming the standards of their profession. Technologies that automate the surface of such tasks while bypassing their situated, relational core risk producing the appearance of authenticity without its substance.

2.2 Evaluative judgement and feedback literacy

A second strand concerns the purpose of assessment as the development of capability rather than merely its measurement. Tai et al. (2018) define evaluative judgement as the ability to make decisions about the quality of one's own work and that of others, positioning its development as a central goal of higher education and a necessary graduate attribute. Feedback, in this context, is effective only to the extent that students can interpret and act on it, what Carless and Boud (2018) term feedback literacy, and what Boud and Falchikov (2006) frame as assessment for long-term learning. These constructs matter acutely for AI: automated feedback can deliver information rapidly, but information is not feedback until it influences future performance. Bearman et al. (2024) argue that developing evaluative judgement becomes increasingly important, not less so, in an era of generative AI, as graduates must assess the quality and trustworthiness of machine-produced work.

2.3 Sociotechnical and sociomaterial perspectives

A third strand resists the notion of AI as a neutral instrument. Sociotechnical accounts assert that tools embed the assumptions, data, and power relations of their creators, and that their effects manifest in use rather than in design (Selwyn, 2019). Baker and Hawn (2022) demonstrate how bias infiltrates educational algorithms through unrepresentative training data and proxy variables, resulting in systematically different outcomes for various groups. Bearman, Nieminen, and Ajjawi (2023) provide an organising framework for designing assessment in a digital world that balances security, authenticity, and learning. From this perspective, the question is never simply whether an AI tool "works," but for whom, under what conditions, with what data, and with what consequences for trust and professional development.

2.4 An integrative analytic framework

Synthesising these strands produces the analytic framework used to interpret the evidence. AI-driven assessment in WIL is evaluated along two axes: a capability axis (efficiency, scalability, personalisation, and feedback quality) and an integrity axis (authenticity, fairness, transparency, academic integrity, and the preservation of human evaluative judgement and professional competence). A tool is deemed beneficial to WIL only when gains on the capability axis do not compromise the integrity axis. This framework directly aligns with the four research questions and structures the results that follow.

3. Methodology

A systematic review design was adopted to identify, appraise, and synthesise the available evidence in a transparent and reproducible manner. The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021). Due to the heterogeneity of the included studies, which encompass empirical evaluations, systematic and meta-reviews, and conceptual analyses, a narrative (qualitative) synthesis was employed instead of meta-analysis, as the latter would have been unsuitable for non-comparable designs and outcomes.

3.1 Research questions

The review was organised around the four questions stated in the introduction (RQ1–RQ4), addressing capability (efficiency, scalability, personalisation), authenticity and integrity, fairness and transparency, and professional competence and human judgement.

3.2 Eligibility criteria

Inclusion and exclusion criteria were specified a priori and are summarised in Table 1. Studies were eligible if they (a) examined an AI-based, automated, or learning-analytics approach to assessment, feedback, or competency evaluation; (b) were situated in higher education, WIL, or professional/work-based education; (c) were peer-reviewed empirical studies, systematic or meta-reviews, or substantive conceptual or policy analyses; and (d) were published in English between January 2015 and June 2025. The timeframe began in 2015 to capture the contemporary wave of machine learning and analytics applications. Studies were excluded if AI was incidental, if the context was outside post-secondary education, or if the item was a brief editorial, abstract, or non-retrievable report.

Table 1: *Inclusion and Exclusion Criteria*

Parameter	Inclusion	Exclusion
Focus	AI/automated/analytics-based assessment, feedback, or competency evaluation	AI absent or incidental to the study
Context	Higher education, WIL, professional or work-based education	Primary/secondary schooling or non-educational settings
Publication type	Peer-reviewed empirical study, systematic/meta-review, or substantive conceptual/policy analysis	Editorials, abstracts, blogs, or non-retrievable reports
Time frame	January 2015 – June 2025	Published before 2015
Language	English	Languages other than English

3.3 Information sources and search strategy

Five databases were searched in June 2025: Scopus, Web of Science, ERIC, EBSCOhost (Education Research Complete), and the ACM Digital Library. These were selected to span the educational, social science, and computing literature. The search combined three concept blocks using Boolean operators: an AI block (“artificial intelligence” OR “machine learning” OR "automated" OR "learning analytics" OR "generative AI" OR "large language model"), an assessment block ("assessment" OR "feedback" OR "grading" OR "evaluat*" OR "competenc*"), and a context block ("higher education" OR "university" OR "work-integrated learning" OR "placement" OR "internship" OR "work-based learning" OR "professional"). Searches were supplemented by backward and forward citation chaining of key papers and by hand-searching two specialist outlets: the International Journal of Work-Integrated Learning and the Journal of Learning Analytics.

3.4 Selection process

All records were imported into a reference manager and de-duplicated. Titles and abstracts were screened against the eligibility criteria, after which full texts of potentially relevant reports were retrieved and assessed. The flow of records through identification, screening, and inclusion is reported in Figure 1. Out of 1,175 records identified (1,148 from databases and 27 from other sources), 271 duplicates were removed, and 904 records were screened. After excluding 762 records based on titles and abstracts, 142 reports were sought, of which 9 could not be retrieved. The remaining 133 full-text reports were assessed for eligibility; 113 were excluded with reasons provided, leaving 20 studies for inclusion in the synthesis.

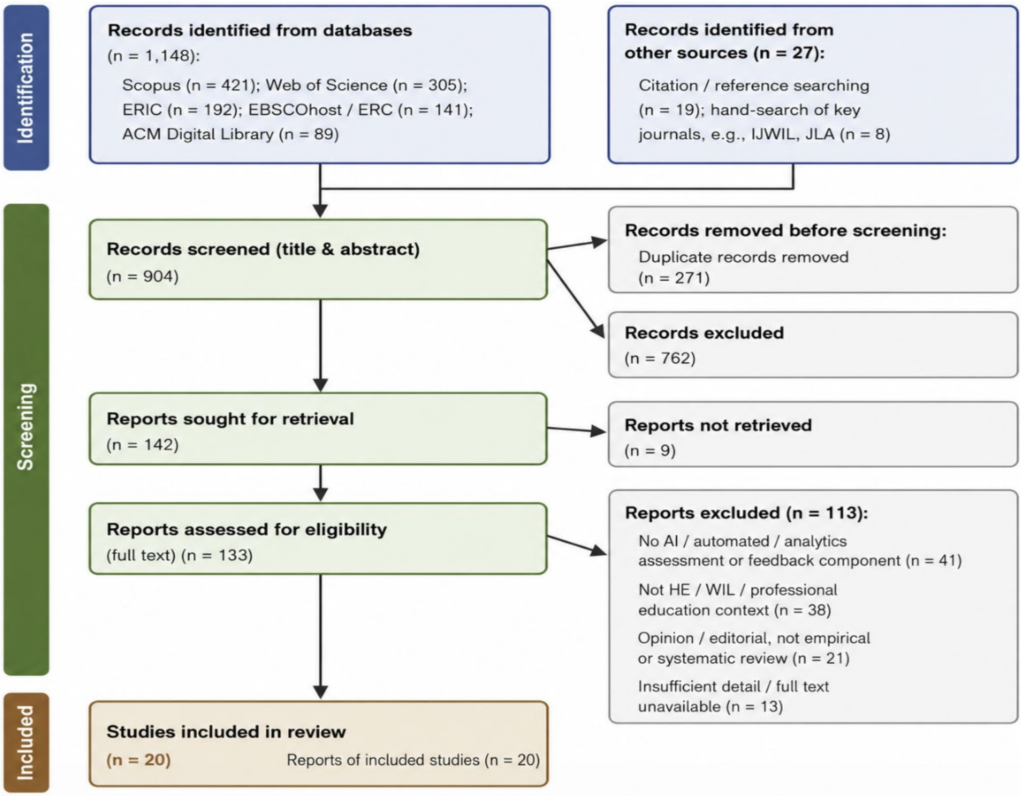

Figure 1 *PRISMA 2020 Flow Diagram of the Study Selection Process*

Note. Adapted from Page et al. (2021). Counts in this diagram correspond exactly to the 20 studies listed in Table 3 below.

3.5 Data extraction and synthesis

A standardised extraction template captured bibliographic details, the country of the lead author, the educational context and discipline, the AI method or tool, the assessment or feedback focus, the study design, and key findings relevant to the four research questions. Extracted data were charted (see Tables 2 and 3) and synthesised narratively. Findings were coded against the capability and integrity axes of the integrative framework, and recurring patterns were grouped thematically under the four research questions.

3.6 Quality appraisal and reflexivity

Because the corpus was methodologically diverse, the appraisal was tailored to the type of study: empirical studies were assessed based on the clarity of aims, appropriateness of design, and warrant for claims; reviews were evaluated on search transparency and synthesis rigour; and conceptual or policy works were judged on argumentative coherence and grounding in evidence. No study was excluded solely on quality grounds; however, the appraisal informed the weight assigned to each source in the synthesis. As a single-reviewer synthesis, the review is limited in its capacity to cross-check screening decisions; this limitation is revisited in Section 6.

4. Results

The 20 included studies were published between 2017 and 2025, with a notable concentration from 2021 onwards, reflecting the increased interest following advances in natural-language processing and the public release of generative AI tools (Figure 2). The corpus comprised four empirical primary studies, seven systematic or meta-level reviews, and nine conceptual, framework, or policy works. Research output was predominantly from Australian and United Kingdom scholars, with additional contributions from continental Europe, North America, and Latin America. Thematically, the studies were evenly divided across four foci: automated feedback and writing analytics; AI-based assessment and analytics; authenticity and integrity under generative AI; and field-level reviews of ethics, bias, and competence (Table 2). Table 3 presents the full characteristics of each included study.

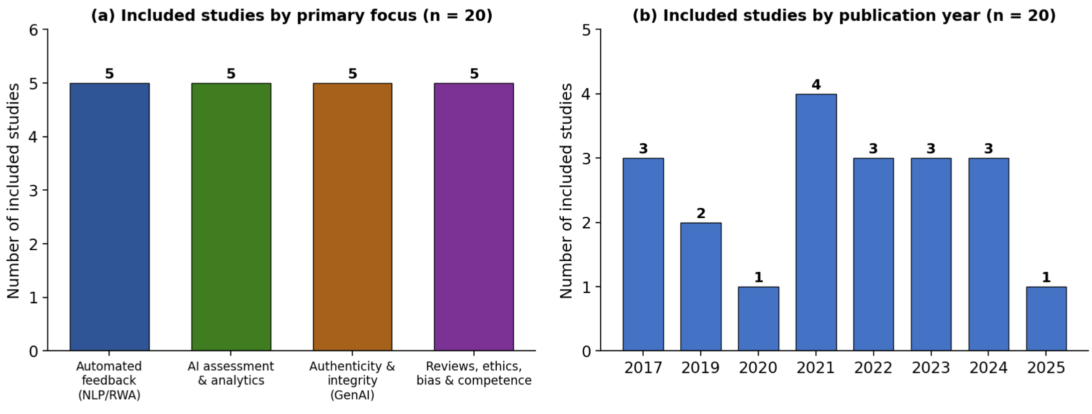

Figure 2: Distribution of the 20 included studies by primary focus and publication year

Note. Panel (a) shows the number of studies by primary focus; panel (b) shows the number by publication year. Counts in both panels sum to the 20 included studies.

Table 2: *Summary Characteristics of the Included Studies (N = 20)*

Characteristic	Category	n
Publication type	Empirical primary study	4
	Systematic or meta-review	7
	Conceptual, framework, or policy	9
Primary focus	Automated feedback / writing analytics	5
	AI-based assessment and analytics	5
	Authenticity and integrity (generative AI)	5
	Reviews of ethics, bias, and competence	5
Region (lead author)	Australia	9
	United Kingdom	4
	Continental Europe	3
	North America	3
	Latin America	1
Publication year	2017–2025 (range)	20

As Table 2 indicates, the corpus is methodologically and geographically diverse. It comprises four empirical primary studies, seven systematic or meta-reviews, and nine conceptual, framework, or policy works, evenly distributed across the four primary foci and predominantly sourced from Australian and United Kingdom scholarship between 2017 and 2025. To transition from this aggregate profile to the evidence itself, Table 3 provides a study-by-study overview of all 20 included studies, detailing each study's context and discipline, AI focus and method, research design, and key findings in relation to the relevant research questions.

Table 3: *Overview of the 20 Included Studies*

Author (year)	Context / discipline	AI focus & method	Design	Key findings (RQ relevance)
Gibson et al. (2017)	Pharmacy/nursing reflective writing; AUS HE–WIL	NLP reflective writing analytics for actionable feedback	Design-based empirical	Automated rhetorical-move feedback scaffolds reflection at scale when co-designed with rubrics (RQ1).
Buckingham Shum et al. (2017)	Reflective writing across disciplines; HE	Rationale & methodology for reflective writing analytics	Conceptual + preliminary validation	Feasible but bounded; human interpretation of depth remains essential (RQ1, RQ4).
Knight et al. (2020)	Academic & reflective writing; HE	AcaWriter learning-analytics feedback tool	Multi-case implementation	Adoption depends on pedagogic co-design; augments rather than replaces educators (RQ1, RQ4).

Luckin (2017)	General education/assessment	Vision for AI-based assessment systems	Conceptual commentary	AI enables continuous assessment but needs ethical framing; deskilling risk (RQ1, RQ4).
Cavalcanti et al. (2021)	Online higher education	Automatic feedback systems	Systematic literature review	Feedback often improves performance; little evidence of reduced workload (RQ1).
Deeva et al. (2021)	HE & online learning	Automated feedback systems taxonomy	Systematic review & framework	Maps system types and challenges of transferability and validity (RQ1, RQ3).
González-Calatayud et al. (2021)	Higher education	AI for student assessment	PRISMA review (22 studies)	Formative assessment and auto-grading dominate; wider contexts needed (RQ1).
Gardner et al. (2021)	Educational assessment (AES, CAT)	Critical appraisal of AI in assessment	Critical review	Validity, transparency, fairness under-examined; cautions over-claiming (RQ3).
Swiecki et al. (2022)	HE assessment	AI-enabled assessment design	Conceptual/agenda review	Calls for redesign and learner agency; flags fairness & over-automation (RQ2–RQ4).
Darvishi et al. (2022)	HE peer assessment	AI + learning analytics for peer assessment	Large-scale empirical	AI and analytics improve reliability and accountability of peer feedback (RQ1, RQ3).
Zawacki-Richter et al. (2019)	Higher education	AI applications in HE	Systematic review (146 studies)	Few studies engage ethics or pedagogy: "where are the educators?" (RQ4).
Bond et al. (2024)	Higher education	AI in HE (meta-level)	Meta systematic review	Calls for greater ethics, collaboration, and rigour (RQ4).
Crompton & Burke (2023)	Higher education	State of AI in HE	Systematic review	Rapid growth; ethical and assessment work comparatively thin (RQ4).
Baker & Hawn (2022)	Education incl. assessment	Algorithmic bias	Conceptual review/synthesis	Documents sources/mechanisms of bias; urges measurement & mitigation (RQ3).
Holmes et al. (2019)	Education	AI in education overview	Foundational synthesis (book)	Frames promises and ethical implications; warns against deskilling (RQ4).

Lodge et al. (2023)	Australian HE	Assessment reform for AI	Policy/guidance report	Recommends programmatic, authentic, human-centred reform (RQ2, RQ4).
Bearman et al. (2024)	Higher education	Evaluative judgement & generative AI	Conceptual	Developing evaluative judgement is central to assessment with GenAI (RQ4).
Dawson et al. (2024)	Higher education	Validity vs cheating framing	Conceptual	Reframes integrity through validity; AI heightens need for valid inference (RQ2).
Bearman, Nieminen & Ajjawi (2023)	Higher education	Designing assessment in a digital world	Conceptual framework	Balances security, authenticity, and learning (RQ2).
Kofinas et al. (2025)	UK business higher education	Generative AI & authentic-assessment integrity	Empirical	GenAI can undermine authentic-assessment integrity; redesign & AI literacy needed (RQ2).

Note. AES = automated essay scoring; CAT = computerised adaptive testing; GenAI = generative artificial intelligence; NLP = natural-language processing; RQ = research question; WIL = work-integrated learning. The 20 studies listed here correspond exactly to the included count in Figure 1.

Read together, Tables 2 and 3 form the evidential basis for the synthesis that follows. Drawing directly on the findings catalogued in Table 3, the next four subsections (Sections 4.1 to 4.4) answer the review's research questions in turn, addressing efficiency, scalability, and personalisation (RQ1); authenticity and academic integrity (RQ2); fairness, bias, and transparency (RQ3); and professional competence and human judgement (RQ4), before Section 4.6 draws the threads together across the analytic framework.

4.1 RQ1: Efficiency, scalability, and personalisation

The most notable benefits reported across the corpus pertain to efficiency and timeliness. Cavalcanti et al. (2021), in their review of automatic-feedback systems in online learning, found that the majority of studies (approximately two-thirds) indicated enhanced student performance following the provision of automated feedback. However, they also concluded that there was limited evidence to suggest that such systems alleviated instructor workload, an important consideration for institutions seeking to achieve cost efficiencies. Deeva et al. (2021) proposed a classification framework for automated feedback systems and catalogued their potential for scalable, immediate feedback, alongside challenges relating to transferability and validity. In the context of WIL, particularly in reflective writing, Gibson et al. (2017) and Knight et al. (2020) demonstrated that natural-language analytics (specifically, the AcaWriter family of tools) can provide actionable formative feedback on reflective and academic writing at a scale unattainable by human markers, provided that these tools are co-designed with educators to ensure alignment between detected features and assessment criteria. Buckingham Shum et al. (2017) similarly emphasised that while reflective writing analytics is feasible, it is also bounded: the technology is capable of identifying rhetorical moves but lacks the ability to evaluate the depth or sincerity of reflection. González-Calatayud et al. (2021), in their review of 22 studies, found that formative assessment and automatic grading were the predominant applications of AI in student assessment, with personalisation emerging as a recurring promise. A consistent pattern emerges across these studies: AI is most convincingly effective in augmenting human feedback on well-structured, text-based tasks, while its efficiency gains are real but narrower and more conditional than vendor claims suggest.

Two qualifications are frequently noted and are particularly relevant to WIL. First, the efficiency observed in the production of feedback does not necessarily translate into increased efficiency for educators or into learning gains for students; Cavalcanti et al. (2021) found no consistent evidence that automated feedback reduced instructor workload, and Deeva et al. (2021) observed that many systems remain limited, domain-specific, and difficult to transfer across various contexts. In WIL, where tasks are diverse and discipline-specific, this restricted transferability presents a significant constraint. Second, the level of personalisation offered by AI is contingent upon the constructs that the system is capable of modelling. The AcaWriter studies illustrate this point: the tool provides feedback on rhetorical structure and reflective markers, which, while valuable, are only partial proxies for the depth of professional insight that reflection in WIL aims to cultivate (Buckingham Shum et al., 2017; Gibson et al., 2017; Knight et al., 2020). Consequently, the case for the efficiency of AI is strongest for formative, low-stakes, text-rich tasks and weakest for the holistic, situated judgements that are essential for demonstrating competence in the workplace.

4.2 RQ2: Authenticity and academic integrity

The arrival of generative AI has unsettled the authenticity of assessments more profoundly than any previous tool. Kofinas et al. (2025), in an empirical study of authentic assessments in a United Kingdom business school, demonstrated that generative AI can be used to circumvent assessment designs intended to be "cheat-resistant," compromising their integrity and prompting calls for redesign and explicit AI literacy. Dawson et al. (2024) reframed the issue theoretically, arguing that institutions are preoccupied with cheating when the deeper issue is validity: an assessment matters because it licenses an inference about competence, and AI threatens that inference whether or not "cheating" has occurred. Bearman et al. (2023) offered a design response, proposing that assessment in a digital world be organised around the interplay of security, authenticity, and learning rather than security alone. For WIL specifically, these findings are double-edged. Authentic, situated tasks, observed performance on placement, supervisor judgement, and integrated practice are more resistant to generative AI than decontextualised written products, which strengthens the case for genuinely work-embedded assessment (Ajjawi et al., 2020; Villarroel et al., 2018). Yet where WIL is assessed through portfolios, reflective journals, or reports, generative AI can fabricate plausible artefacts, threatening the personal authenticity on which professional reflection depends.

The literature also directs attention towards constructive responses rather than mere alarm. Swiecki et al. (2022) assert that an appropriate reaction to AI necessitates a reconsideration of what and how assessments are conducted, advocating for a shift towards tasks that emphasise process, agency, and knowledge integration, characteristics that are more challenging to counterfeit and are more aligned with the objectives of WIL. Lodge et al. (2023), in their advisory role to the Australian regulator, recommend a programmatic approach in which integrity is assured across an entire programme of authentic, scaffolded assessment, rather than being defended on a task-by-task basis. When considered alongside the authentic-assessment literature, these sources suggest that generative AI does not so much invalidate WIL assessment as increase the difficulty of conducting it superficially: portfolio-and-reflection models that are loosely supervised become vulnerable, whereas models grounded in observed performance, interactive vivas, and supervisor verification become comparatively more defensible (Ajjawi et al., 2020; Dawson et al., 2024).

4.3 RQ3: Fairness, bias, and transparency

Concerns regarding fairness are prevalent throughout the corpus. Baker and Hawn (2022) provided the most systematic examination, documenting the ways in which algorithmic bias infiltrates educational systems through unrepresentative training data, proxy variables, and feedback loops, and how it can result in systematically different outcomes for learners with varying language backgrounds, ethnicities, or socioeconomic statuses. Gardner et al. (2021) cautioned that enthusiasm for automated essay scoring and adaptive testing has outstripped scrutiny of their construct validity, transparency, and fairness, warning against "buncombe and ballyhoo." Similarly, Swiecki et al. (2022) identified fairness, transparency, and the risk of over-automation as central challenges for assessment in the age of AI. The transparency problem is structural: many high-performing models are opaque, making it difficult for students to contest an automated judgement or for assessors to explain it, a serious concern in WIL, where assessment decisions can gatekeep entry to a profession. Darvishi et al. (2022) offered a more optimistic counterpoint, showing that combining AI with learning analytics can make peer-assessment systems more trustworthy and accountable, suggesting that careful design can mitigate rather than amplify unfairness. The balance of evidence indicates that AI does not remove human bias so much as relocate and sometimes conceal it, making auditability and the right to human review essential safeguards.

4.4 RQ4: Professional Competence and Human Judgement

The fourth theme addresses whether AI enhances or undermines the human judgement integral to professional competence. The field-mapping reviews exhibit remarkable consistency. Zawacki-Richter et al. (2019), in their review of 146 studies, identified an "almost complete absence" of critical reflection on the risks associated with AI in education and a weak connection to pedagogical theory, poignantly questioning, "where are the educators?" Bond et al. (2024), in a meta-review of reviews, echoed this concern, advocating for increased focus on ethics, collaboration, and methodological rigour. Crompton and Burke (2023) confirmed rapid growth in the field while observing that ethical and assessment-focused research remained comparatively sparse. In light of this, several authors contend that AI should be positioned to enhance rather than replace judgement. Bearman et al. (2024) argue that fostering students' evaluative judgement, their ability to assess the quality of work, including that generated by machines—should be a primary educational objective in the era of generative AI, echoing the sentiments of Tai et al. (2018). Lodge et al. (2023), in guidance for the Australian regulator, advocate for programmatic, authentic, and human-centred assessment reform rather than a regression into surveillance. Luckin (2017) and Holmes et al. (2019) foresee genuine benefits from AI-based assessment but caution against deskilling if educators relinquish interpretive authority to systems. The synthesis indicates that professional competence is best achieved when AI manages pattern detection and routine feedback, while human assessors retain responsibility for contextual, holistic, and high-stakes judgements, endorsing a human-in-the-loop model rather than full automation.

5. Synthesis Across the Analytic Framework

Mapping the findings onto the integrative framework reveals a clear structure. On the capability axis, the evidence is moderately positive and concentrated: AI reliably improves the timeliness and reach of formative feedback and can support personalisation and the scaling of peer assessment (Cavalcanti et al., 2021; Darvishi et al., 2022; Knight et al., 2020). On the integrity axis, however, the evidence is more cautionary and diffuse: threats to authenticity and validity (Dawson et al., 2024; Kofinas et al., 2025), documented bias and opacity (Baker & Hawn, 2022; Gardner et al., 2021), and a field-wide neglect of ethics and educators (Bond et al., 2024; Zawacki-Richter et al., 2019). Crucially, the studies that report the strongest capability gains are also those that insist most firmly on human co-design and oversight, while the studies that raise the gravest integrity concerns are those examining automation without such safeguards. The two axes are therefore not independent: integrity is the condition under which capability gains become legitimate. This relationship anchors the discussion that follows.

6. Discussion

6.1 A Conditional verdict

Read against the integrative framework, the evidence supports a qualified and conditional verdict. On the capability axis, AI tools demonstrably improve the speed, scale, and consistency of feedback, especially for text-based and reflective tasks that are central to WIL pedagogy (Cavalcanti et al., 2021; Gibson et al., 2017; Knight et al., 2020). They can personalise formative feedback and, when paired with learning analytics, strengthen otherwise fragile practices such as peer assessment (Darvishi et al., 2022). These are not trivial gains in a sector under workload pressure. However, on the integrity axis, the same tools introduce risks that fall precisely on the dimensions WIL most needs to protect. Generative AI destabilises the authenticity and validity of written WIL artefacts (Dawson et al., 2024; Kofinas et al., 2025); opaque models threaten transparency and the right to contest a judgement (Gardner et al., 2021; Swiecki et al., 2022); and bias can disadvantage the linguistically and culturally diverse learners that WIL programmes often serve (Baker & Hawn, 2022).

The central implication is that the value of AI in WIL assessment depends almost entirely on whether it is positioned to augment or replace human evaluative judgement. Where AI handles pattern detection, surface-level writing feedback, and the logistics of feedback at scale, while human assessors retain responsibility for contextual, holistic, and high-stakes decisions, the capability gains can be realised without sacrificing integrity (Bearman et al., 2024; Lodge et al., 2023). However, where AI is treated as a substitute for professional judgement, automating competency decisions or grading reflective practice without human oversight, the integrity costs are likely to outweigh the efficiency benefits. This human-in-the-loop principle reframes the apparent dichotomy between efficiency and authenticity as a design question rather than a forced choice.

6.2 Implications for the higher education–workplace relationship

These conclusions highlight a larger shift in the relationship between universities and employers. WIL acts as the institutional hinge between the two, and assessment is where the university discharges its warranting function to the profession and the public. AI complicates this warrant in two opposing ways. On one hand, generative tools mean that some traditional indicators of competence, such as polished reports and written reflections, no longer reliably demonstrate what a student can do unaided, weakening the signal that employers have historically relied upon (Dawson et al., 2024; Kofinas et al., 2025). On the other hand, the workplace itself is being reshaped by AI, so that the competence graduates need increasingly includes the ability to work critically and ethically with AI tools. Developing students' evaluative judgement serves a dual purpose: it protects the integrity of assessment and builds a capability that the contemporary workplace demands (Bearman et al., 2024; Tai et al., 2018). In this context, Work-Integrated Learning (WIL) is not merely threatened by AI; rather, it is a privileged site for cultivating the discernment required for working alongside AI.

6.3 From detection to validity-centred design

The findings also reframe academic integrity. Rather than an arms race of detection and surveillance, the more durable response is to redesign assessment so that validity is robust to AI (Dawson et al., 2024). WIL is comparatively well placed here: situated performance, observed practice, and supervisor judgement are intrinsically difficult to outsource to a machine. This supports the argument for deepening genuinely work-embedded assessments rather than retreating to invigilated examinations (Ajjawi et al., 2020). At the same time, the persistence of bias and opacity means that fairness cannot be assumed; it must be designed, measured, and audited, with accessible avenues for human review (Baker & Hawn, 2022).

Finally, the review echoes a recurring critique of the wider field: AI in education has too often been developed and evaluated without placing educators, pedagogy, or ethics at the centre (Bond et al., 2024; Zawacki-Richter et al., 2019). In WIL, where the stakes include licensure, public safety, and professional identity, this absence is untenable. The evolving relationship between higher education and the workplace will be shaped less by the raw capabilities of AI than by whether institutions embed it within defensible assessment principles.

7. Limitations

Several limitations qualify these conclusions. First, the literature specific to AI in WIL assessment is limited; much of the evidence is drawn from higher education assessment more broadly and is mapped onto WIL, which may overstate its transferability to placement and workplace settings. Second, the corpus is dominated by Australian and United Kingdom scholarship and by English-language sources, which limits cultural and linguistic generalisability, an irony given the review's concern with bias. Third, the field is moving quickly: generative AI capabilities have changed substantially within the review window, so some empirical findings may date rapidly. Fourth, the synthesis was conducted by a single reviewer, which constrains the reliability of screening and extraction relative to a multi-reviewer protocol; the search counts and selection decisions reported here should be read as a transparent account of one reviewer's process rather than as an inter-rater validated result. Finally, the decision to include conceptual and policy works alongside empirical studies, while appropriate for an emerging and contested topic, means that some conclusions rest on reasoned argument rather than primary data.

8. Implications and Recommendations

Four recommendations follow for practice and policy. First, adopt human-in-the-loop designs: use AI for formative feedback, drafting, and pattern detection, while reserving summative and competency judgements for human assessors who can consider context and professional standards (Bearman et al., 2024; Lodge et al., 2023). Second, it is imperative to pursue validity-centred assessment reform rather than detection-centred responses, by redesigning WIL assessment around observed and situated performance that is intrinsically resistant to automation (Dawson et al., 2024). Third, equity and transparency should be fundamental components of procurement and deployment: it is essential to require evidence of bias testing, ensure appropriate explainability commensurate with the stakes involved, and establish an accessible right to human review prior to the deployment of any AI tool in consequential assessments (Baker & Hawn, 2022; Gardner et al., 2021). Fourth, it is crucial to cultivate the AI and evaluative-judgement literacy of both students and staff, enabling graduates to critically appraise machine-generated work and educators to co-design tools that align with assessment criteria (Carless & Boud, 2018; Tai et al., 2018). In terms of research, the priority should be empirical, longitudinal, and equity-focused studies of AI in authentic WIL settings, conducted collaboratively with educators and workplace partners rather than upon them.

9. Conclusion

AI-driven assessment and feedback present significant but conditional value for work-integrated learning. The evidence compiled in this review indicates that AI can facilitate faster, more scalable, and more personalised feedback, particularly for reflective and written tasks that bridge academic study and professional practice. However, it also demonstrates that AI has the potential to undermine the authenticity, fairness, transparency, and human judgement that are essential for credible professional formation. The solution does not lie in uncritical adoption or blanket prohibition, but rather in deliberate design: strategically positioning AI to augment human evaluative judgement, reforming assessment practices to ensure that validity remains resilient against automation, and prioritising equity and transparency as non-negotiable conditions of use. If higher education maintains a central focus on educators, students, and professional standards, AI can enhance the assessment of WIL rather than diminish it, thereby strengthening, not weakening, the connection between the university and the workplace.

10. Declarations

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Artificial intelligence has transitioned, in a remarkably short period, from the periphery of educational discourse to the very centre of our conceptualisation of teaching, learning, and the preparation of students for professional life. Nowhere are the stakes of this shift higher than in Work-Integrated Learning, the domain where the classroom intersects with the workplace and where the promise and perils of new technologies are experienced most acutely. This book was conceived in response to this pivotal moment, stemming from a conviction that the question confronting educators is no longer whether AI will reshape Work-Integrated Learning, but rather how, for whom, and at what cost. It brings together scholars who have chosen to address this question directly, with curiosity, rigour, and a shared commitment to the students and communities their work ultimately serves.

The chapters compiled herein approach the challenge from multiple perspectives. They encompass teacher education, chemistry, information and communications technology, early childhood education, and educational management; they draw on evidence from South Africa, Nigeria, Zimbabwe, and beyond; and they utilise methods as diverse as bibliometric mapping, systematic review, qualitative case study, conceptual analysis, and autoethnography. What unites them is the set of commitments encapsulated in the book's title. The contributors assert that innovation must be pursued thoughtfully rather than embraced uncritically; that equity must remain central, ensuring that AI broadens rather than narrows access to meaningful learning; and that genuine progress relies on partnerships, between institutions and workplaces, between educators and technologies, and across the Global North and the Global South. When considered collectively, the chapters provide both a sober account of the risks and a hopeful, practical vision of what AI-enhanced Work-Integrated Learning could become.

This collection is the result of the generosity, patience, and scholarship of numerous individuals. I am profoundly grateful to the authors, who entrusted their work to this project and responded graciously to the demands of revision; to the reviewers, whose meticulous and constructive engagement strengthened each chapter; and to the ERRCD Forum, whose commitment to open and accessible scholarship has made this book freely available to readers wherever they may be. It is my hope that students, researchers, educators, and policymakers alike will find in these pages both a critical map of our current position and a constructive sense of potential pathways forward. More importantly, I hope the book serves as an invitation, to question, to experiment responsibly, and to continue the dialogue about how artificial intelligence can be harnessed to serve, rather than undermine, the profoundly human endeavour of education.

Cias T. Tsotetsi
Editor