Gordon Institute of Business Science
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LLMs in Corporate and Institutional Knowledge Transfer: Rethinking Knowles and Bloom

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Abstract

This qualitative study explored how LLMs affect Knowles's Andragogy and Bloom's Taxonomy within a corporate or institutional knowledge transfer context. The study specifically focused on the adult learner.

An exploratory and inductive methodology was employed through the process of semi-structured interviews. Participants were senior professionals who were acknowledged AI leaders in their organization and regularly required to impart knowledge.

The literature review and thematic analysis revealed that LLMs act as enablers of andragogical principles, but this effect is conditional upon the learner's intent to learn compared to task completion. It was also found that LLMs transform Bloom's linear hierarchy into an iterative feedback loop. This feedback loop necessitated the development of a new questioning layer. The questioning layer was found to be dependent on the learners' ability to critically evaluate, validate and self-reflect LLM output.

The study's main contribution lies in providing a conceptual link between Knowles' Andragogy and Bloom's Taxonomy. Informed by the proposed intent condition for Knowles' Andragogy and the questioning layer for Bloom's Taxonomy in LLM-augmented environments.

Key words

Large Language Models (LLMs), Adult Learning, Knowles's Andragogy, Bloom's Taxonomy, Leaner Intent

Plagiarism Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1.1 Background

Business is entering an era of rapid transformation. The arrival of generative artificial intelligence (GenAI) or better known as Large Language Models (LLM) is fundamentally changing how knowledge is accessed and applied (Cappelli et al., 2024; Marone, 2025; Yee et al., 2025)

Yee et al. (2025) likens the impact of LLMs to be as influential as the steam engine was to the Industrial Revolution. Leaping from the automation of tasks to the automation of cognitive tasks (Yee et al., 2025).

The impact of this revolution is emphasised by the significant investment garnered from corporations. As a recent report by McKinsey indicates, more than 92% of companies plan to increase investment in AI (Yee et al., 2025). This same report also estimated that the potential long-term value generated due to AI adoption will peak at $4.4 trillion (Yee et al., 2025).

Thus, GenAI should not be thought of us as a peripheral technology, only used by a select few. McKinsey reports that nearly a quarter of C-suite executives acknowledged using LLMs for their day-to-day work (Yee et al., 2025).

Equally, leaders in corporate training also expect LLMs to have a significant impact. Marone (2025) reported in a recent Havard Business Impact study, that Learning and Development leaders (L&D) overwhelmingly expect LLMs to improve their talent development. Likewise, these leaders also expect that LLMs will make learning more scalable and adaptable (Marone, 2025).

The perceived benefit of LLMs is thus evident. It’s not difficult to imagine that in an era where entire industries are transformed, the competitive differentiator will be organisations that can upskill at scale (Marone, 2025).

The integration of LLMs into everyday life is also not limited to the corporate world. Foster & Borrett (2025) reports in the Financial Times that over 90% of university students already admitted to using LLMs in their studies. This rapid adoption by learners is prompting experts to call for urgent reform.

Understandably, a recent article by Nature challenged the use of essays and take-home assignments. Questioning its capacity to reflect genuine intellectual effort (Yang, 2023). Thus, LLMs are fundamentally challenging long-held assumptions about how learning should be structured and evaluated (Kohler, 2024; Valcea et al., 2024).

1.2 Research Problem

1.2.1 The Business Problem

Rapid adoption of LLMs by employees has created a disconnect between current corporate strategy and employee behaviour. A McKinsey survey in 2024 found that a mere 13% of employees considered their companies to be early LLM adopters (Relyea et al., 2024). This is even though 9 out of 10 of the same employees reported using LLMs for their work.

Lagging corporate strategy creates an environment where risks are unmanaged and productivity gains are not measured or even fully realised. This strategic gap illustrates how rapidly knowledge transfer in business has changed. The mismatch is also mirrored in the differences between traditional corporate training methods and the new reality of how employees learn with LLM (Marone, 2025).

This leads us to the core business problem, current knowledge transfer frameworks are built on models that see knowledge passed down linearly from an expert to a novice (Espinoza, 2025). In contrast, an employee can now produce work at a complex level, without needing to go through the step-by-step learning that traditional training methods prescribed (Gonsalves, 2024; Valcea et al., 2024).

At the same time, the ability to get information from an LLM instantly, negates the andragogical principle that experience or context is a pre-requisite to learning (Elim, 2024; Gonsalves, 2024). Thus, conventional training approaches are out of touch with the non-linear way LLMs allow knowledge to be transferred.

LLMs are thus changing the need for employees to know vast amounts of content. Skills are rather evolving to mastering processes like critically evaluating LLM outputs and problem-solving (Espinoza, 2025). Unfortunately, current L&D models are not designed to build these skills, leaving companies unable to leverage LLMs into a competitive advantage.

1.2.2 The Theoretical Problem:

The need for a transformation in how knowledge is transferred in business is also reflected in adult education. Our main frameworks for learning, Knowles's Andragogy and Bloom's Taxonomy were developed in the 20th century (Elim, 2024; Gonsalves, 2024). The issue isn't that learning has stopped. It's that learning now happens in ways these models weren't built to describe.

Malcolm Knowles's Andragogy suggests that adults learn best when they are self-directed, can draw on their experience and see the immediate use of the knowledge (Knowles et al., 2014). Bloom's Taxonomy, in both its original and updated versions, presents cognitive growth as a linear ladder or a pyramid. A person must master lower-order skills like Remembering before they can use higher-order skills like Analysing or Creating (Anderson & Krathwohl, 2001; Bloom, 1956).

LLMs disrupt these ideas. As highlighted earlier, a learner using an LLM can generate output at the Create level of Bloom's hierarchy without engaging any of the foundational steps (Elim, 2024; Gonsalves, 2024). This doesn't mean learning is skipped. It means the process is likely flipped. A learner can Evaluate the AI's output, Analyse it and in doing so build their own Understanding of the topic (Jain & Samuel, 2025). Learning is still happening, just not in the linear steps of the old frameworks.

Knowles et al. (2014) argues that adults use their prior experience as a motivator for learning. An LLM which offers instant expertise, seems to challenge this. However, it could be argued that it does not devalue prior experience, it just changes its function. Instead, a person's experience becomes a critical filter to judge whether the AI's answers make sense in the real world (George et al., 2025).

Siemens (2005) helps to put this problem into context, in his theory of connectivism, he thought of knowledge as not held inside a person but spread across network of people and technology. Learning is then the act of building these networks (Siemens, 2005). Similarly, Clark & Chalmers (1998) theorised in the theory of the Extended mind, that thinking extends outside of the individual, into tools. This fits well with how learners experience LLMs, as a highly accessible information network.

On the other hand, Knowles's Andragogy and Bloom's Taxonomy see knowledge as something an individual acquires and holds internally. This difference leaves a major gap. We need a new framework that can make sense of how learning happens in this hybrid space, where knowledge is actively transferred between a person and an LLM.

1.3 Purpose and Objectives of the Study

The purpose of this exploratory, inductive study is to investigate how the integration of LLMs in corporate knowledge transfer affects the theoretical validity and practical applicability of Knowles's Andragogy and Bloom's Taxonomy.

This research asks if these frameworks still hold up now that LLMs augment various cognitive tasks. The aim is to develop a new conceptual framework to guide adult learning in this hybrid cognitive environment.

The research addresses the urgent need to ensure that learning strategies in professional and executive education are aligned with the new realities of human-AI collaboration. (Elim, 2024; Gonsalves, 2024). The objectives of the study are as follows:

1. Evaluate how LLM use impacts Knowles's six andragogical principles in a corporate or institutional context.

2. Analyse how LLM-enabled learning disrupt Bloom's hierarchical structure in a corporate or institutional context.

3. Identify the new competencies required for effective knowledge transfer in LLM-augmented environments.

4. Synthesise these findings to inform both frameworks to illustrate adult knowledge transfer in LLM-augmented environments.

1.4 Scope of the Study

This study focuses on adult learning within corporate and business education. It specifically looks at how LLMs affect two foundational theories, Knowles's Andragogy and Bloom's Taxonomy.

The empirical data is derived from the perceptions and lived experiences of a purposively selected sample of twelve senior professionals and educators in South Africa. They are chosen for their expertise as early adopters or designated leaders in AI integration within their organisations.

The study is restricted in several ways. It does not aim to produce a statistically generalizable model applicable to all learning contexts but rather to generate a context-dependent theoretical contribution. The research also does not evaluate the technical performance of specific LLM platforms, nor does it measure learning outcomes. The nature of the study provides a snapshot in time and does not track learner perceptions as AI technology advances.

1.5 Structure of the Report

This research report is structured into seven chapters to present a logical and coherent argument.

- Chapter 1 introduced the research problem. It established the business and theoretical need and summarised the purpose and scope of the study.
- Chapter 2 will provide a review of the relevant academic literature. It will critically argue why Knowles' Andragogy and Bloom's Taxonomy were analysed. Explore their revisions and compare them with newer or different theories. Finally, it will explore the competencies required in LLM-augmented learning environments.
- Chapter 3 will present the research questions that emerge from the literature review.
- Chapter 4 will outline and defend the research methodology. Justify the reason for an exploratory, inductive and qualitative approach and outline the methods for sampling and data collection.
- Chapter 5 will present the empirical findings of the study, which are organized into the key themes that emerged from the thematic analysis of the interviews.
- Chapter 6 will interpret the findings in relation to the literature review and the research questions.
- Chapter 7 will summarise and present the principal findings and offer recommendations for organisations and future research.

Chapter 2:
Literature Study

2.1 Major Learning Constructs

Adult learning forms a critical part of corporate training programs. (Mukhalalati & Taylor, 2019) identifies seven main theories to describe the various adult learning theories that exist. These are cognitive, humanistic, transformational, social, motivational, reflective and constructivist theories.

It is also important to recognize that there is significant overlap in the understanding of how learning happens between the various theories. For instance, constructivist theories that emphasise active learner engagement is also central in transformation and social learning theories (Mukhalalati & Taylor, 2019).

Cognitive learning is based on the structuring of mental processes to master skills and apply knowledge practically. It can be represented as the scaffolding of mental frameworks, where learners progress from understanding facts to synthesizing strategies for complex problems (Biggs, 1979; Bloom, 1956; Irvine, 2017; Mukhalalati & Taylor, 2019; Wu, 2023). In an adult environment, this would likely unfold where managers learn financial modelling through guided instruction, build comprehension and then applying the relevant mental frameworks to assess market risks.

Humanistic learning champions self-directed growth. Empowering learners to align education with personal aspirations. This theory aims to nurture a student's intrinsic drive. In turn this is believed to allow them to shape their own learning journeys (Fink, 2003; Knowles et al., 2014; Mukhalalati & Taylor, 2019; Peno, 2024). In short, learners develop relevance by creating personal leadership plans, choosing projects or learning experiences that promote their broader life goals.

Transformative learning beliefs that critical examination of experiences orients learner perspectives. It fosters innovative thinking as learners need to reconstruct professional identities to navigate uncertainty (Alam, 2022; Dirkx, 1998; Mukhalalati & Taylor, 2019). This is best shown with adults who experienced corporate failures and reframed their management strategies to be more sustainable

Social learning thrives on the collective knowledge created through shared interactions. It can be best viewed as a network of exchanges between a group of people, and the group dynamics are believed to amplify innovation (Adams, 2010;

Amin & Roberts, 2006; Mukhalalati & Taylor, 2019). A practical example could include simulations of business scenarios, where leaners have an opportunity to co-construct knowledge with their peers.

Motivational learning cultivates learner persistence by aligning learning with psychological needs. It emphasizes psychological incentives tied to achievements. (Mukhalalati & Taylor, 2019; Ryan & Patrick, 2009). Students demonstrate this by choosing projects linked to personal goals.

Reflective learning argues that a student's understanding is improved by purposefully processing experiences. It can be described as a cyclical dialogue between action and insight (Kolb & Kolb, 2012; Mukhalalati & Taylor, 2019; Schon & DeSanctis, 1986). An illustration would be a when students reflect on negotiation outcomes intrinsically and adapt their tactics for future scenarios.

Constructivism argues that knowledge is created when learners interact with prior experiences and social environments. The theory sees learning as a context dependent process. It is alternatively described as the holistic approach where learners build meaning from internal mechanisms and external (Chaves, 2008; Merrill, 2017; Mukhalalati & Taylor, 2019; Wu, 2023). In this case, when students take part in debating scenarios with peers, they are intrinsically and extrinsically reflecting and learning in a group context.

Table 2-1 provides a consolidated summary of these major theoretical constructs and their representative theories.

Table 2-1:

Learning Constructs

Learning Constructs	**Learning Theories**	**Contribution**
Cognitive	Bloom's Taxonomy, Bloom (1956)	Hierarchical classification of cognitive skills from knowledge to evaluation, foundational for curriculum design.
	SOLO Taxonomy, Biggs (1979)	Assesses structural complexity of learning outcomes. Linking study processes to cognitive depth.
	New Taxonomy, Marzano (Irvine, 2018)	Expands cognitive hierarchies with metacognition and self-system, contrasting with Bloom's for performance improvement.

Humanistic	Andragogy, Knowles	Model for adult learning emphasizing self-direction, experience-based relevance, and intrinsic motivation.
	Self-Directed Learning (SDL), Peno (2024)	Process where adults take initiative and responsibility for education, focusing on autonomy and lifelong adaptability.
	Significant Learning, Fink (2003)	Course design model promoting holistic, personally relevant experiences to foster self-efficacy and meaningful change.
Trans-formative	Transformative Learning, Mezirow (Dirkx, n.d.)	Critical reflection to challenge assumptions and reconstruct perspectives
	Transformative Learning Framework, Alam (2022)	Conceptualization using critical reflection for sustainable development and responsible citizenship.
Social	Communities of Practice (CoPs), Lave & Wenger (Amin & Roberts, 2006)	Situated learning through shared practices and interactions in social contexts.
	Action Learning, Revans (Adams, 2010)	Group-based questioning and reflection to solve real-world problems collaboratively.
Motivational	Self-Determination Theory (SDT), (Ryan et al., n.d.)	Focuses on intrinsic motivation via autonomy, competence, and relatedness needs.
Reflective	Reflective Practice, Schön (1984)	Reflection-in/on-action to adapt tacit knowledge in professional contexts.
	Experiential Learning Theory (ELT), Kolb & Kolb (2008)	Reflective observation as a key stage in the learning cycle.
Constructivist	Dialectical Constructivist Approach, Chaves (2007)	Active knowledge construction via thesis-antithesis-synthesis for learning transfer.
	First Principles of Instruction, Merrill (2018)	Problem-centred construction of knowledge through real-world integration.

2.2 Cognitive and Humanistic Theories

The emergence of AI in professional settings has put emphasises on skills that are uniquely human. This study emphasizes cognitive and humanistic theories because generative AI (GenAI) most disrupts individual learning pathways in corporate settings, where personal insight and motivation remain irreplaceable.

Today's professionals are flooded with data and AI-generated insights. Cognitive theories are essential in this setting, because it promotes critical thought and not just information recall (Relyea et al., 2024). LLMs are becoming increasingly proficient at lower-order tasks like retrieving and summarizing. In that case the human competitive advantage shifts decisively to the upper levels of Bloom's hierarchy, analysing, evaluating and synthesizing.

Valcea et al. (2024) warns however of an Expertise Paradox. Indicating that AI's competence in basic tasks might weaken the scaffolding of cognitive ability and affect a learner's development of their higher-order skills. This prompts an examination into cognitive frameworks like Bloom's to understand how to preserve higher order human skills in the AI era.

The elements in Humanistic theories, on the other hand, is unable to replicate AI (Mukhalalati & Taylor, 2019). Corporate employees need more than technical skill, they need motivation, self-direction, the necessary habits and the right environment to support learning (Fink, 2003; Knowles et al., 2014; Peno, 2024). However, LLM's are creating a fundamental shift in outlook from adults. Adults and learners in general can still be self-directed, but will be faced with either relying on an LLM to complete a task or learning the skill themselves (Tomaszewska, 2023).

Cognitive and humanistic theories align well with the study's goals because LLMs are arguable bypass these theories mechanisms. Whereas the mechanisms in social, reflective, constructivist and even transformational theory are all heavily supported through an LLM's ability to develop simulations and to provide instant feedback(Wu, 2023). Thus, the mechanism still remains the same for these theories, it is just supported by LLMs.

2.3 Humanistic Theory: Knowles's Andragogy

Knowles's six principles of Andragogy outline that adults view themselves as self-directed individuals, who are ready to learn when real-life demands. Compared to children they have extensive experience to rely on. It also argues that adults prefer problem centred rather than content orientated learning and respond better when they are intrinsically motivated. Finally, adults seek a clear 'why' behind the reason to absorb content (Knowles et al., 2014).

Table 2-2:

Knowles's Six Core Assumptions of Andragogy (Knowles et al., 2020)

Principle	**Core Assumption**
The Need to Know	Adults are motivated to learn when they understand *why* they need to learn something.
The Learner's Self-Concept	As individuals mature, they move from dependency toward being self-directed.
The Role of the Learner's Experience	Adults bring a vast reservoir of experience to learning.
Readiness to Learn	Adults are ready to learn things they need to know to cope with real-life situations.
Orientation to Learning	Adult learning is problem-centred rather than content-oriented.
Motivation	The most potent motivators are internal pressures like job satisfaction or self-esteem.

This focus on motivation sets Knowles's andragogy apart. It makes it suited for corporate contexts where adults juggle various demands when considering upskilling (Storey & Wagner, 2024).

Brief comparisons with other humanistic frameworks emphasise this difference. Peno (2024) self-directed learning (SDL) focuses more on traits or habits that will support the process of learning in adults. Thus, SDL describes how to learn when you are a self-directed individual, whereas Knowles explains the motivations behind why learning occurs.

Fink's (2003) significant learning is a broad holistic theory, focused on knowledge, application, human ties, caring and self-learning. The Significant learning theory is non-hierarchical and provides emotional depth. Arguably, Fink' (2003) focuses on what will sustain self-learning. Knowles can once again be likened to the 'why' Adults learn in their professional lives.

These differences highlight why Knowles andragogy was preferred for this study. It better describes the conditions that will motivate an adult to initiate learning (Tomaszewska, 2023). This emphasis provides a lens to study how LLMs could erode an adults' intrinsic drive to learn.

Holton et al. (2001) further developed the Knowles Andragogy by introducing a layer or a precondition. It was referred to as ‘Goals and purposes for learning’. Holton et al. (2001) argued that individual differences, situational factors and specific learner goals also shape learning. Conceptually this layer is applicable in the age of LLMs, as these factors will likely determine if a self-directed learner uses an LLM or puts in the effort to learn the skill.

2.4 Cognitive Theory: Bloom's Taxonomy

While andragogy defines the adult learner (Knowles et al., 2014), the cognitive pillar of learning has been defined by Bloom's Taxonomy (Bloom, 1956)(Bloom et al., 1956). A framework that classifies the cognitive objectives that define learning itself.

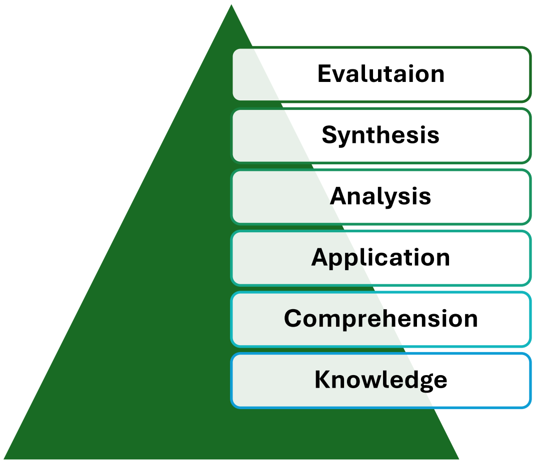

Figure 1:

Bloom’s Taxonomy Pyramid, developed from (Bloom, 1956)

As per Figure 1 it organises these cognitive objectives into a sequential hierarchy of Knowledge, Comprehension, Application, Analysis, Synthesis and Evaluation. Progressing from lower to higher-order thinking. It assumes that mastery of each lower tier is needed to progress or engage with higher levels.

Bloom’s model exists however within a wider conversation of theories, each trying to map the learning process. Where Bloom's taxonomy provides a qualitative process classification of cognitive outcomes(Bloom, 1956), other theories offer a procedural roadmap.

For instance, Biggs (1979) Structure of the Observed Learning Outcome Taxonomy (SOLO) assesses the outcome and the quality of the learning process. It describes five ascending levels of understanding with pre-structural as the first level, where the student focuses on irrelevant information. Then, Uni-structural is when the student focuses on one relevant aspect to his learning objective. Multi-structural is when the student lists several relevant aspects but is unable to integrate them yet. On the relational level, the student integrates the parts into a coherent whole and understands the concept. The final level is extended abstract, where the student can extrapolate his understanding to a different context.

Merrill's (2017) First Principles of Instruction in contrast to both SOLO and Blooms argued that learning is problem-centred, not content orientated. This model cycled through phases of activation of prior knowledge, demonstration of the new skill, application of the skill and integration. Merrill (2017) principles mimics real world learning but it fundamentally still describes the procedure of learning and not qualitative process steps like Blooms.

Marzano's New Taxonomy is a systems-based model that argues that cognition is driven by higher-order systems (Irvine, 2017). At the top is the self-system which comprises a learner's belief and emotions, basically describing his motivation whether to even engage. When the self-system is engaged, the metacognitive system then sets goals and strategies. Only then is the cognitive system activated to process the information. The cognitive system itself contains a hierarchy with retrieval, comprehension, analysis and knowledge utilization.

Marzano's New Taxonomy differs to the First principle of instruction and SOLO taxonomy as it incorporates both a qualitive and a procedural aspect. Blooms however is more discerning theory and describes high order thinking even more granular detail (Bloom, 1956). This makes Blooms a more appropriate theory to analyse the effect of LLMs, as literature expects lower order thinking to be most affected and humans' proficiency in Higher order thinking to be even more crucial (Relyea et al., 2024).

2.5 Revision of Bloom's Taxonomy

Anderson & Krathwohl (2001) argued that the original first step in Bloom's, Knowledge, stood out from the rest of the steps. That the other steps described a process of cognition and that knowledge was an outlier. He reasoned that knowledge represents the content that a leaner needs to think about at each individual level.

Anderson & Krathwohl's (2001) major revision corrected this by removing 'Knowledge' and replacing it with the verb 'Remember', which better represents a process of cognition. All the other levels were also replaced with verbs and Anderson & Krathwohl (2001) swapped the top two levels, placed Synthesis or now Create at the peak of the cognition pyramid, Table 2-3

Table 2-3:

The Revised Bloom's Taxonomy, (Anderson & Krathwohl, 2001)

Revised Bloom's Taxonomy
Remember
Understand
Apply
Analyse
Evaluate
Create

Furthermore, Anderson & Krathwohl (2001) then conceptualised that Knowledge, is still a critical factor to the learning process. They expanded this single category into its own a second dimension, the Knowledge Dimension. This new dimension asks what type of knowledge the learner is acting upon at each level of cognition. Breaking the knowledge factor into factual, conceptual, procedural and metacognitive see Table 2-4

Table 2-4:

New Knowledge Dimension, (Anderson & Krathwohl, 2001)

Factual Knowledge:	The basic elements of a discipline, its terminology, and specific details.
Conceptual Knowledge:	The interrelationships between those elements, such as principles, models, and theories.
Procedural Knowledge:	The "how-to" of a subject, including skills, techniques, and methods.
Metacognitive Knowledge:	Knowledge *about* cognition, including strategic awareness and self-knowledge about one's own learning processes.

This two-dimensional matrix created a grid where any cognitive process from the first dimension could be paired with any type of knowledge from the second dimension Anderson & Krathwohl (2001). This allowed for a more nuanced understanding of each cognition level.

2.6 Digital-Age Adaptations of Blooms Taxonomy

To account for the realities of modern professional life, Churches's (2010) proposed a new ‘Digital Taxonomy’. Churches's (2010) Taxonomy attempted to translate new digital behaviours into the existing Bloom levels. For example, Remembering is given a more digitally prescriptive word such as ‘bookmarking’ and Creating is described by ‘podcasting’.

Churches’ (2010) more significant contribution was the proposal to add an entirely new competency. Churches (2010) argued for the inclusion of Collaboration as a new level, see Table 2-5, citing the prominence of the internet and how it affects modern life. He recognized that adult learning was shifting from an intrinsic act to a more networked and social process.

Passig (2003) also contributed to the conversation by introducing a skill that he argues will be crucial in the future. His study was responding to the perceived fear that current theories cannot accurately account for the effect of Information Technology (IT) on learning. Interestingly his argument mirrors conversations today about LLMs. He reasoned that yes, IT does promote more engagement with higher cognition, but that it also provides individuals with more ways to execute.

This led to him coining a new skill, melioration, see Table 2-5. It is the ability to pull from the concepts and tools available and consciously decide and apply the combination relevant to the problem you are being faced with.

Table 2-5 :

Digital Age adaptions of Bloom’s Taxonomy

Passig (2003)	**Churches (2010)**
Knowledge	Remembering
Comprehension	Understanding
Application	Applying

Analysis	Analysing
Evaluation	Evaluating
Synthesis	Creating
Melioration	Collaboration

These examples of pre-GenAI adaptations are critical to reflect upon, because technology is forcing learning to become increasingly extrinsic. Attempts at adapting such a prolific theory indicate that there is a fear that Bloom’s cannot accurately reflect this change (Churches, 2010; Gonsalves, 2024; Hmoud & Ali, 2024; Passig, 2003).

2.7 The Impact of LLMs on Andragogy

Passig (2003) argued that IT provides individuals the more ways to execute. It could be argued that AI promotes this even more so. The principles of andragogy then, with its emphasis on self-direction and problem-centred learning, seem almost perfect to be disrupted by an LLM.

For instance, Adarkwah (2024) highlighted how LLMs can deliver personalised learning and immediate feedback, aligning perfectly with the adult learners’ requirements. Marone (2025) similarly stressed that already, by embedding in the workflow, learning powered by LLMs is amplifying performance at scale.

Storey & Wagner (2024) however emphasised AI Educational (AIED) systems carry a subtle risk. Arguing that algorithmic biases are prevalent in LLM models and that these biases in AIED systems can amplify perceived and actual disparity. This risk’s perpetuating inequalities for underrepresented groups in a corporation and even novices. Possibly actually eroding internal motivation and self-direction for these adult learners.

This concern raised by Storey & Wagner (2024) is also mirrored by Valcea et al. (2024), who termed a phrase ‘Expertise Paradox’. Valcea et al. (2024) reasoned that because LLMs are able to complete lower-level cognitive tasks more efficiently than humans could. It will likely weaken the development of students' of higher-level thinking. The very efficiency of an LLM disincentives adult learners to engage in the cognitive steps required to build knowledge.

This effect is particularly damaging for trainees and novices, who lack the prior experience needed to critically evaluate an AI's output. The same tool that accelerates andragogical principles can thus simultaneously undermine an adult learners goal of genuine expertise development.

To counter this, experts have advocated for robust guidelines to promote educator-AI partnerships and ethical use can foster human-centred integration. Ensuring GenAI supports rather than supplants adult learners' intrinsic drive (Adarkwah, 2024)

2.8 The Impact of LLM's on Bloom's Taxonomy

Literature suggests that GenAI does not only superficially change the name of the cognition levels or add an abstract new step. It probably inverts its structure fundamentally (Elim, 2024). This inversion implies students can rapidly generate output without the necessary depth and comprehension.

The mechanism for this disruption is again linked to Valcea's et al. (2024) concept of an expertise paradox. Because an LLM allows a learner to begin their journey at the very top of the taxonomy.

Arguably, an inexperienced businessman can prompt an LLM to create a business plan and then use that generated output as a scaffold to work down the pyramid (Elim, 2024; Valcea et al., 2024). Analysing the application of the concepts and ultimately using it to understand the foundational principles.

Elim (2024) proposes a version of the above conceptual model. Where the stages of questioning, feedback and reflection repeat in a feedback loop until the learner is satisfied. This addition of an iterative nature transforms the fixed pyramid into a dynamic model where learners can move fluidly between levels.

A more radical reconceptualization is offered by Jain & Samuel (2025). They argue that the current cognitive levels in the revised taxonomy are too simplistic to reflect the complex engagements in a LLM augmented environment.

Jain & Samuel (2025) proposes a level below 'remembering', what he refers to as 'ventriloquising'. It is described as the process where a learner imitates or replicates LLM-generated information without internalizing it. Furthermore, Jain & Samuel's (2025) model also replaces the last step creating with co-curating. Reasoned that it helps to describe the distinct collaborative and iterative process of knowledge creation with an LLM partner.

Gonsalves (2024) revision of the taxonomy, takes this arguably even a step further. The proposed model expands on Bloom's Cognitive domain and introduces a new affective and metacognitive domain. The affective domain includes skills like collaborating and ethical reasoning with AI. The new metacognitive domain, however, specifically captures the non-linear learning process by introducing skills like interrogating and refining, iterative learning, meliorating and reflective thinking.

Some proposed models propose a less radical changes to Bloom. The AIEd Bloom's Taxonomy proposed by Hmoud & Ali (2024) rather tries to capture how learners would interact with LLMs. The model, Collect, Adapt, Simulate, Process, Evaluate and Innovate retains the original linear hierarchy and does not imply an iterative process as with the others.

Overwhelmingly, the literature that attempted to map learner cognition in LLM augmented environments, perceived and found significant changes to the hierarchical and linear nature of Blooms, prompting further investigation (Elim, 2024; Gonsalves, 2024; Jain & Samuel, 2025).

2.9 New Theoretical Lens to Explain the Disruption

Knowledge is increasingly created and shared through human and machine interactions. Bloom's Taxonomy however, considers different cognitive objectives as intrinsic milestones (Jain & Samuel, 2025). To understand how these milestones can possibly be met in this context, we need to look at theories that explain these interactions better.

Siemens (2005) for instance, describes a world where knowledge exists in a network rather than solely within the learner. The theory, Connectivism, does not see learning as the accumulation of content but the ability to navigate and evaluate connections. Reasoning that competency depends less on what professionals know and more on their capacity to access and interpret distributed expertise.

An LLM strengthens this mechanism by introducing a new responsive intelligent node into Siemens' implied network, capable of re-organising information and interacting with the learner. This heightened interactivity transforms learning from an act of simple recall into an iterative conversation with the network (Elim, 2024; Gonsalves, 2024).

Clark & Chalmers' (1998) takes this a bit further with their extended mind hypothesis. This theory proposes that cognition extends beyond the boundaries of the brain. The theory famously presents the 'Otto' example, an Alzheimer's patient who needs to rely on a notebook to navigate a city's street. Effectively the notebook becomes an extension of himself and becomes part of his memory Clark & Chalmers' (1998).

Lodge et al. (2023) also noted a similar observation when learners interact with LLMs. He remarks that it acts as a prosthesis, that not only supports but amplify human capability. Gerlich (2025) referred to this cognitive prosthesis more appropriately as cognitive offloading. Defining cognitive offloading as the delegation of mental operations such as remembering and analysing to technological aids.

However, Gerlich (2025) argued that there is both advantages and risks through this process. On the positive side, it frees up cognitive resources for higher-order tasks and creative problem-solving, but dependence can erode reflective engagement and lead to what he terms as cognitive laziness (Gerlich, 2025). This concern also aligns with Valcea's et al. (2024) expertise paradox, where LLMs' proficiency in low-order cognitive tasks erodes the deliberate preparation required for higher-order reasoning.

Clark & Chalmers (1998) however does a imply condition to the extended mind theory. He argues that extended cognition is only possible when the external system is trusted and reliably available. However, more recent literature adds another dimensionality to that condition. Lodge et al. (2023) showed that effective co-regulation with AI depends on continuous monitoring and evaluation. Storey & Wagner (2024) likewise reasoned that LLMs must be coupled with critical thinking. This was also reinforced by Yusuf et al. (2024), who showed that learners must critically evaluate and validate AI-generated information.

These theories indicate that the interactions between the learner and LLMs will require ongoing internal reflection and critical evaluation. Without it, the interaction becomes a dependency rather than augmentation (Valcea et al., 2024).

2.10 Andragogy: Learner Goals and purposes

As mentioned earlier, Knowles expanded his andragogical framework and introduced a model a contextual layer of goals and purposes for learning (Holton et al., 2001). He recognised that personal drive and the surrounding context shaped how adults choose to learn.

Espinoza (2025) argues that LLM's allows adults to be more selective of their goals, promoting their self-relevance even more. This is possible because LLMs provide adults the ability to adjust the content, it's pace and feedback. Essentially adapting the learner experience for the best outcome.

Storey & Wagner (2024) also points out the importance for educators to promote learner reflection and ethical judgement. Highlighting the importance for the technology to remain only a partner in thought rather than a substitute for it.

The study by Atanassova & Cabori (n.d.) captures this relationship clearly. Their findings shows that outcomes improve only when learners used AI purposefully. When AI was used casually, reasoning weakened and collaboration suffered. They conclude that technology empowers or impairs depending on how intentionally it is woven into the learning process.

That finding echoes Holton's claim that context and purpose ultimately decide the quality of adult learning (Holton et al., 2001). Although he never specified the layer to be conditional, only as a contextual guidance. Literature does point to the fact this might be the case.

2.11 Core Competencies

Anderson & Krathwohl (2001) revision of Bloom's taxonomy introduced a metacognitive dimension that focuses on awareness and regulation of one's own thinking. It implies that learners must not only remember and apply information but also monitor and evaluate how they are learning. Passig (2003) also proposed melioration, describing it as the conscious selection of tools to solve complex problems. Both concepts position reflection and evaluation as essential to move to a higher-order cognition.

Similarly, Jain & Samuel's (2025), revision of the framework argue that large language models transform learning from a linear sequence into an iterative cycle of collaboration between human and machine. Gonsalves (2024) also expands Bloom's hierarchy by adding a metacognitive and affective domain that emphasises the need for ethical reasoning, interrogation, and reflective thought when working with AI-generated outputs.

Lodge et al. (2023) also observed habits of learners who engage productively with AI and referred to it as co-regulation. He indicated that these students monitored their goals, evaluated system responses and adjusted their strategies as an interaction unfolds.

Yusuf et al. (2024) emphasises the need for adults to verify and interpret AI outputs critically. Storey & Wagner (2024) emphasise the importance of reflection and ethical judgement of LLM output. Ng et al. (2021) mirrored both by requiring a student to have AI literacy, which includes assessing outputs critically and considering the ethical implications.

Across these studies, three abilities recur, engaging critically with information, validating and verifying AI-generated content and reflecting on how technology shapes one's own reasoning (Jain & Samuel, 2025; Ng et al., 2021; Storey & Wagner, 2024; Yusuf et al., 2024). These competencies can be understood as practical enactments of the metacognitive and meliorative dimensions

Learning with an LLM depends less and less on the skills necessary to access it. Increasingly, more important is the learner's capacity to stay mentally active within the process.

2.12 Conclusion

The literature reviewed in this chapter traces a clear thread, unpacking various over-arching adult theories. It is argued that cognitive and humanistic learning theories are the most appropriate constructs to analyse knowledge transfer in corporate settings.

Within the humanistic branch, Knowles andragogy stood out, because it was more motivation orientated, focusing on why adult learners decide to learn(Holton et al., 2001; Knowles et al., 2014). In the cognitive branch, the focus was on Blooms Taxonomy and the revised Bloom's taxonomy. In contrast to the other theories, Blooms taxonomy and its revision was more focused on the learner's cognitive milestones, whereas the other theories were more procedural focused (Anderson &

Krathwohl, 2001; Bloom, 1956). While Knowles explains the motivational conditions for learning, Bloom provides a framework for the development of cognitive complexity

Revisions of Knowles' andragogy also followed. The revision recognised that an adult's motivation is particularly influenced by both internal drive and situational context, illustrating it as an overarching layer (Holton et al., 2001). In this literature study it's positioned that LLM's provide a conditionality to this layer, if a student's goal is to complete the task without learning, then there will be no motivation to absorb the knowledge.

This layer in Knowles is also mirrored in the metacognitive dimension of the revised Bloom's taxonomy and Passig's later addition of melioration (Anderson & Krathwohl, 2001; Passig, 2003). Both constructs emphasising self-awareness and the ability to adapt decision-making according to the learner's context.

Furthermore, other contemporary theories were also analysed to help understand the mechanism when learning with an LLM, helped the researcher to put the competencies required in context. Theories such as connectivism and the extended mind explain how learning now occurs through interaction with distributed and intelligent systems (Clark & Chalmers, 1998; Siemens, 2005). While these perspectives help describe where learning happens, they pay less attention to how adults regulate that process.

More recent literature begins to address this gap, showing that AI can reinforce learner motivation when used purposefully. It also demonstrates that unreflective use can weaken reasoning and collaboration (Atanassova & Cabori, n.d.; Gonsalves, 2024; Jain & Samuel, 2025; Lodge et al., 2023; Ng et al., 2021; Storey & Wagner, 2024; Yusuf et al., 2024). Collectively, these studies indicate that AI neither guarantees nor prevents learning, it amplifies the learner's underlying orientation.

Despite this growing body of work, a clear framework explaining adult knowledge transfer in LLM-augmented environment does not exist. There is scant research specifically about andragogy in AI. The current literature is more focused on the competencies to use an LLM and various process or systems it can be integrated into(Adarkwah, 2024; Storey & Wagner, 2024; Tomaszewska, 2023). It does not investigate an adult's motivation to actually absorb information in an LLM-augmented environment.

Current adaptions of Blooms, are mostly shallow reflections, changing the name of the Bloom’s levels to reflect a process when using an LLM (Churches, 2010; Gonsalves, 2024; Hmoud & Ali, 2024). Few identify new process, just ancillary additions to the accepted Bloom’s taxonomy(Jain & Samuel, 2025). Furthermore, none of these theories specifically reflect on adult learners.

Thus, no integrated theory explains why an adult would be motivated to absorb knowledge in an LLM augmented environment and how would these adults reach different cognitive milestones in this environment.

Chapter 3
Research Questions

3.1 Introduction

The purpose of this chapter is to synthesise the gaps that were identified in the literature study in Chapter 2. Whereafter these gaps will then be consolidated into research questions that aims to guide the study. The research questions ultimately link the research problem in Chapter 1, the literature study in Chapter 2 and the methodology in Chapter 4, (Saunders & Lewis, 2018).

3.2 The research gap

The research problem identified that LLM's are being rapidly adopted by adult learners in corporate and institutional contexts. However, the literature review highlighted that our frameworks for adult learning and cognitive development have not kept pace. From the literature review two primary, interconnected gaps can be identified.

<u>Research gap 1:</u> The literature review highlights that research on Knowles's Andragogy in the age of AI is scarce. It also presents that Knowles Andragogy is built on an adult's internal motivation to learn to solve real-world problems. LLMs introduce a contradiction, it allows an adult to solve a problem without necessarily engaging in the cognitive effort of learning. This raises a fundamental question, whether Knowles's principles of self-concept and motivation are still relevant in LLM augmented environments. Thus, does LLM's promote or retard the Knowles's framework.

<u>Research gap 2:</u> In contrast to andragogy, the literature on Bloom's Taxonomy is more developed, with several authors arguing that LLMs invert the pyramid or even fundamentally break its linear structure. However, many of these proposed revisions are theoretical or surface level adaptions. A gap still exists in understanding how this non-linear, iterative process will present within a corporate or institutional context.

This study aims to address these gaps by exploring the authentic experiences of senior leaders who are acknowledged as early AI/LLM adopters in their organisation and required to transfer knowledge (upskill, train, coach, mentor etc.) on a frequent basis.

3.3 Research Questions

To address the gaps identified above, this study will investigate two related research questions:

RQ1: How do LLMs affect Knowles's Andragogical principles within the context of corporate or institutional knowledge transfer?

RQ2: How do LLMs affect Bloom's Taxonomy within the context of corporate or institutional knowledge transfer?

3.4 Alignment with Research Objectives

The research questions developed above aims achieve the primary objectives of the study outlined in Chapter 1.

The first research question, directly addresses the first objective in chapter 1, evaluating how LLM use impacts Knowles's six andragogical principles. The second research question also directly addresses the second research objective 2, analyse how LLM-enabled workflows disrupt Bloom's hierarchical structure.

By answering these two research questions, the study will gather the necessary qualitative data to answer the third objective, identify the new competencies required for effective knowledge transfer in LLM-augmented environments.

This will ultimately inform the study's aim in the fourth objective, synthesising the findings to inform both frameworks to illustrate adult learning in an LLM-augmented environment.

Chapter 4:
Choice of Methodology

4.1 Introduction

The following chapter unpacks the research methodology selected for the study. This chapter guided the researcher by providing a robust framework. This framework ensured that there was alignment between the research question, the research design, the research methodology and ultimately, the findings presented.

4.2 Choice of Research Design

4.2.1 Purpose of Research Design

This study followed an exploratory research design. This was appropriate as the integration of LLMs into adult education is a new phenomenon and literature in this space is scarce(Saunders & Lewis, 2018). This research study approached this by assessing the relevance of Knowles's Andragogical principles and Bloom's taxonomy.

An exploratory study also facilitated the use of semi-structured interviews with individuals involved in knowledge transfer within corporate or institutional training environments (Saunders & Lewis, 2018). This created the opportunity to gather new insights to propose how these frameworks can be modified to eventually account for LLMs' impact on knowledge transfer in a corporate context.

4.2.2 Philosophy

The study aimed to develop an in-depth understanding of how adults learn in LLM-augmented environments by analysing it through two theoretical frameworks, Bloom's taxonomy and Knowles' Andragogical principles. These frameworks are designed to understand the motivations and the various stages of human learning (Anderson & Krathwohl, 2001).

Interpretivism was an appropriate philosophy as the participants were selected because they are social actors in this space (Saunders & Lewis, 2018). Suggestions and modifications that this study proposed was developed from the lived experiences and perspectives of the participants. Due to the nature of the topic, interpretivism allowed the study to capture the unique experiences of the participants in a highly relevant topic (Saunders & Lewis, 2018).

4.2.3 Approach selected

While both frameworks have been adapted and modified, the impact of LLMs on adult learning in corporate and organisational contexts was still underexplored. Thus, it was decided to select an inductive approach, as this study aimed to build new insights and understanding rather than testing existing theories.

The goal was not to build a new theoretical framework but to generate new understandings that informed, critiqued and observe linkages between the existing theories. Through the inductive approach, we developed an authentic understanding of the actual experiences of participants as was directed by Saunders & Lewis (2018). This aligned well with the exploratory nature of the study, as findings was used to interpret Bloom’s Taxonomy and Knowles’s Andragogical principles as per the research questions.

4.2.4 Methodological choices

This qualitative study was developed through a mono-method data collection approach, using semi-structure interviews to capture insights from participants (Saunders & Lewis, 2018).

4.2.5 Strategy

This study adopted a qualitative research strategy using thematic analysis to explore how the selected participants perceived the influence of LLMs on the application of Bloom’s taxonomy and Knowles’ Andragogical principles in adult learning, particularly within corporate and institutional contexts. Thematic analysis allowed for the identification of recurring patterns and commonalities across participants’ insights (Braun & Clarke, 2006)

Through this approach, insights from multiple participants across different organisations and institutions were gathered. This broad sampling will allow the discovery of commonalities, divergences and emerging adaptations in how AI-enhanced learning is perceived and could be applied.

4.2.6 Time horizon

This study was a cross-sectional study which allowed the researcher to take a snapshot of the relevant stakeholders' perception at that point in time (Saunders & Lewis, 2018). The study provided insights from participants at this point in time, as LLMs is still a rapidly evolving technology and tracking changes and perceptions over time would not have been appropriate.

4.3 Proposed Research Methodology

4.3.1 Population

The population included early adopters of artificial intelligence that are often required to transfer knowledge. Because this was an exploratory study, the population was not limited to a single institution, which enabled comparative insight across different contexts (Creswell et al., 2007). This enabled the researcher to gather grounded feedback to inform or critique Knowles's and Blooms' frameworks.

4.3.2 Unit of analysis

The unit of analysis in this study was senior leaders who are considered experts or early adopters of artificial intelligence within their organizations, often required to upskill and transfer knowledge. By studying their experiences and perspectives, the study analysed how adult learning or knowledge transfer is augmented by LLMS (Creswell et al., 2007). The unit of analyses was specific to senior leaders in an organization and included both participants that had a background as a lecturer (structured learning) or had no formal pedagogical training.

The insights gathered from these participants formed the basis to identifying themes and patterns. Themes were then directly linked to inform the specific research question referring to either Knowles's or Bloom's frameworks.

4.3.3 Sampling method and size

Since it is not possible to determine the population size, non-probability sampling will be used (Saunders & Lewis, 2018). Additionally, given the pace at which LLMs are developing, it was expected to be difficult to identify which leader had experience with LLMs. Therefore, a multi-layered approach was taken, using purposive sampling initially and then followed by snowball sampling (Saunders & Lewis, 2018).

The purposive sampling method relied on the researcher's judgement to identify sample members (Saunders & Lewis, 2018). The following criteria was used to approach participants:

1. An acknowledge AI/LLM adopter in his organization or team.
2. Required to transfer knowledge and skills (train, upskill, coach, mentor etc.) on a frequent basis in a corporate or institution.

After the initial round of participation selection, snowball sampling was employed. Snowball sampling was appropriate because it was difficult not only to determine but also approach members of the defined population get appropriate feedback. The initial members were then used to identify the subsequent participants (Saunders & Lewis, 2018).

The scope of the study made homogenous sampling not appropriate (Guest et al., 2006). Stakeholders shared similar characteristics in that they were leaders in a corporate or institution and deemed AI/LLM adopter. But this was not specific to age group, gender or educational background.

The number of participants was determined by the point at which the data reached saturation and no new insightful codes or themes presented themselves. In this case it was 12, aligning with Guest's et al. (2006) finding in qualitative studies.

4.3.4 Measurement Instrument

The qualitative exploratory nature of the study made semi-structured interviews the most appropriate data collection method. This approach allowed the researcher to be intentional in their questioning which provided the ability to maintain a degree of flexibility and explore themes raised in the interview (Saunders & Lewis, 2018).

Golafshani (2003) noted that in a qualitative study, the credibility and reliability of the information is dependent on the researcher. Thus, to ensure consistency, an interview guide was developed. Interview questions were linked to the research questions to ensure that they were grounded in literature and contributed to addressing the research problem, see Addendum C.

Two pilot interviews were also conducted to help refine the interview guide and ensure adequate comprehension of the interview questions(Saunders & Lewis, 2018). Though this process it was gauged necessary to develop a brief introduction to Blooms and Knowles to ensure that the participants all had the same base understanding of the frameworks. This was included in the interview guide and shared with the participant in advance.

4.3.5 Data gathering process

As indicated in the previous section, a series of semi-structured interviews were conducted to collect participant data. The initial selection of participants was through purposive sampling strategy. This involved a targeted search strategy on Linkedin and using the researcher's professional network to get in contact with appropriate participant. The participants were then either contacted through LinkedIn's direct messaging service or their emails.

Following this, referrals (snowball sampling) was used to identify additional relevant participants and for the most part contacted through WhatsApp, LinkedIn or email. When an interview date was set, the participant was sent a Google Meet invite. A consent form was developed that outlined the study's purpose and ensured that all participants provided informed consent before proceeding with the interviews. This was sent to the participant ahead of the interview together with the interview guide

Interviews were conducted in a one-on-one format, recorded and guided by the interview guide. Only one participant was a physical interview that was also audio recorded. However, one particularly relevant participant could not attend an interview due to the participant's schedule. To ensure their valuable perspectives were not lost, the participant provided detail and contextual answers to the interview guide via email correspondence. McArdle (2022) argues that the researcher be pragmatic and flexible, thus this correspondence was included and coded. Since most of the data will be non-text data in an audio or video format, it will have to be transcribed into text data verbatim (Saunders & Lewis, 2018).

Confidentiality will be maintained by not reporting the names of participants. They will be referred to as P1 to P12. Only a brief description of their Additionally, data will be reported as aggregates and any quotes will be reported without any identifiers.

All interview audio files, transcripts, and related research documents will be stored securely for a minimum of 10 years without any unique identifiers. The data will be saved on a secure, access-controlled cloud storage platform**.** Access will be restricted to the researcher through password protection and two-factor authentication. At the end of the retention period, all files will be permanently deleted.

4.3.6 Analysis approach

Since this study adopted a qualitative and inductive approach, thematic analysis was the most appropriate method for identifying patterns and key themes within the data (Braun & Clarke, 2006). Thematic analysis has limited interpretative potential if not coupled with an existing theoretical framework. It was therefore a particularly suitable method to examine Bloom's and Knowles' frameworks in the context of LLM-augmented knowledge transfer (Braun & Clarke, 2006).

The video and audio recordings were transcribed verbatim. A thematic analysis was then applied on the transcribed interviews using ATLAS.ti software. To ensure consistency and theoretical alignment, themes were explicitly coded in line with the research questions. Direct quotations were included to ground interpretations in participants' own words.

The approach used to analyse the data is summarised in Table 4-1:

Table 4-1:

Data Analyses approach phases(Braun & Clarke, 2006)

Phase	Data analyses Approach.
1	Researcher familiarize himself with data by transcribing and reviewing interviews.
2	Generated an initial coding scheme to identify recurring themes using ATLAS.ti Software.
3	Codes were then grouped to identify emerging themes using ATLAS.ti software.
4	Emerging themes were then reviewed to confirm that they form a coherent pattern when combined with the codes and other themes.
5	Thereafter, a description of the theme was developed, which captured the essence of the theme, allowing for key insights.

6	The final step was to produce a report and to ensure that the themes that were developed relate back to the literature and research objectives.

4.3.7 Quality controls

To ensure consistency, this study applies multiple quality control measures, see Table 4-2:

Table 4-2:

Quality Control Measure Steps

Step	Quality control measures
1	An interview guide with a briefing was developed to provide structure and consistency to the interview process (Saunders & Lewis, 2018).
2	Interviews were audio recorded and transcribed.
3	Via the process of active listening and reflective questioning, participants were able to review and confirm answers to ensure an accurate representation of their perspectives (Roulston, 2010)
4	Codes and themes will be cross verified with other participants and with literature, enabling triangulation of data (Golafshani, 2003).
5	Transparency will be maintained by keeping an audit trail of all research, coding and data interpretations (Roulston, 2010).
7	Transferability was maintained by ensuring a clear description of the population and sampling methods that were employed, refer to Table 5-1 (Ahmed, 2024).

4.3.8 Limitations

4.3.8.1 Time Horizon

LLMs' rapid evolution presented a unique limitation, as findings can quickly become outdated and new LLM tools emerge. The study attempted to mitigate this by focusing specifically on the authentic experiences of leaders in corporate or institutional environments.

4.3.8.2 Participant Bias

Participant bias may influence responses, as experts with positive or negative experiences with LLMs may shape their perspectives accordingly. To reduce the effect of this bias, triangulation between multiple participants and literature was developed in Chapter 6 (Golafshani, 2003)

4.3.8.3 Researcher Bias

The researcher's role in data collection and analysis also likely introduced the possibility researcher's bias (Roulston, 2010). To minimize this, strategies such as active listening and reflective questioning, participants were able to review and confirm answers to ensure an accurate representation of their perspectives.

4.3.8.4 Methodological choice

This study was likely restricted by the use if a mono method. The study only analysed the peoples lived experiences qualitatively. More depth could have been gathered through a mixed method approach.

4.3.8.5 Data Collection

The fact that 1 participant was interviewed through email correspondence presented a limitation regarding the lack of in person, verbal communication. This meant it was not possible to use probing questions to explore any new emergent themes.

Chapter 5:
Results

5.1 Introduction

This chapter presents the results developed from the thematic analysis of twelve semi-structured interviews conducted with professionals and educators from various fields. The primary data was coded and analysed through thematic analyses, from which four central themes emerged in response to the research questions.

These themes provide insight into how Large Language Models (LLMs) are perceived to influence the adult learning frameworks of Knowles's Andragogy and Bloom's Taxonomy within a corporate or institutional context. Each theme will be presented in a separate section, substantiated by verbatim quotations from the participant interviews to ensure the findings are grounded in the primary data. The objective of this chapter is to present these results in a clear and organized manner, providing the foundation for the subsequent discussion in Chapter 6.

5.2 Sample Description

The study utilised a purposive and snowball sampling strategy to recruit 12 participants with expertise relevant to the research questions, as specified in the methodology, Chapter 4. Confidentiality was maintained throughout the study. To ensure anonymity, participants are referred to by a participant number (P1 to P12) in this report.

The sampling strategy specifically sought out senior leaders who are considered experts or early adopters of artificial intelligence within their organizations. Some held formal titles such as 'AI adoption lead' or even a designation such as a 'AI adoption champion'.

The sample included participants with a formal background in university lecturing (structured learning) who are now active in the corporate world. This dual-sourcing strategy allowed for rich authentic perspectives from structured educational environments together with those from on-the-job corporate learning contexts, where individuals are often required to upskill and transfer knowledge without a formal pedagogical background.

Table 5-1 provides a detailed profile of each participant, outlining how they align with the study's unit of analysis criteria: holding a leadership position, having a responsibility for knowledge transfer, and an example of how they have adopted Large Language Models (LLMs) at their organisation.

Table 5-1:

Summary of Research Participants

	Role	**Involvement in Adult training**	**Experience with LLM's**
P1	Senior Industrial Practitioner	Required to coach and mentor to transfer industry specific and safety skills. This includes skills like practical programming and data visualization	Uses LLM's to debug code, generate scenario examples and draft learning aids
P2	Process Development Engineer	Facilitates hands-on Data analytics (Power BI/Python) training sessions with assessments for key personnel in operations	Uses LLM's to debug code, data-cleaning assists and documentation review.
P3	R&D Manager	Creates SOPs and standards, Leads 'Engineers In Training development; develops practical operations training tied to plant problems	Uses LLM's to develop training materials, coding and documentation review
P4	Leads a company that designs Technical courses for private companies	Delivers tutoring and technical short courses; develops practical exercises and worked examples. Backgound as a University lecturer/ STEM tutor.	Uses LLM's for lesson prep, scenario questions and solution walkthroughs
P5	AI Adoption Lead Engineer	Designs and runs internal workshops; Training new recruits; Develops SOPs	Selects and rolls out LLM tools; coaches' teams on safe and effective usage of LLM's
P6	University lecturer & supervisor (Engineering)	Designs and Teaches courses for Under and –postgrad; supervises research	Experiments with LLM's for student engagement, course design and rubric drafting
P7	Head of Academics	Leads and trains teachers; oversees curriculum	Explored LLM's for lesson prep and uses

	(Secondary School)	development and educational strategy.	LLMs for providing student feedback
P8	Director of Operations for major industrial company	Coaches employees; co-creates learning artefacts; works with suppliers on capability building	Designated AI Champion for company; Built various AI tools for company to use
P9	Co-Owner & CEO of a Machine vision and AI solutions company	Training new recruits on company IP; training and influencing potential clients	Develops AI products and Uses LLM's particularly as a “thinking partner” to structure ideas
P10	Head of digital learning content in healthcare	Manages content team; builds online modules and clinical decision-support training. Background as a University lecturer	Uses LLM's for first drafts and structuring of content
P11	Owner of an Advanced Process Control Company	Translates control theory into practical plant application; Coaches operators/technicians/engineers; develops diagnostic tools	Regularly uses it to draft standards and training plans; Helps him supports multilingual teams; Building an LLM-enabled Root Cause Analysis Tool (RCAT);
P12	Owner & CEO of a Process engineering consulting company and Honorary lecturer & PhD supervisor.	Provides metallurgical and thermochemistry training to clients through consulting company; Supervises PhD research.	Uses LLMs to offload drafting/admin while concentrating on judgment and synthesis; promotes principled use around peers

5.3 Data Gathering Process

The data from the twelve semi-structured interviews was analysed using an inductive thematic analysis approach. A codebook was developed, with codes being generated from the initial interviews and then applied and refined throughout the analysis of the subsequent data. This process continued until thematic saturation was reached.

To demonstrate this process, Figure 2 below illustrates the number of new codes that were generated during the analysis of each interview.

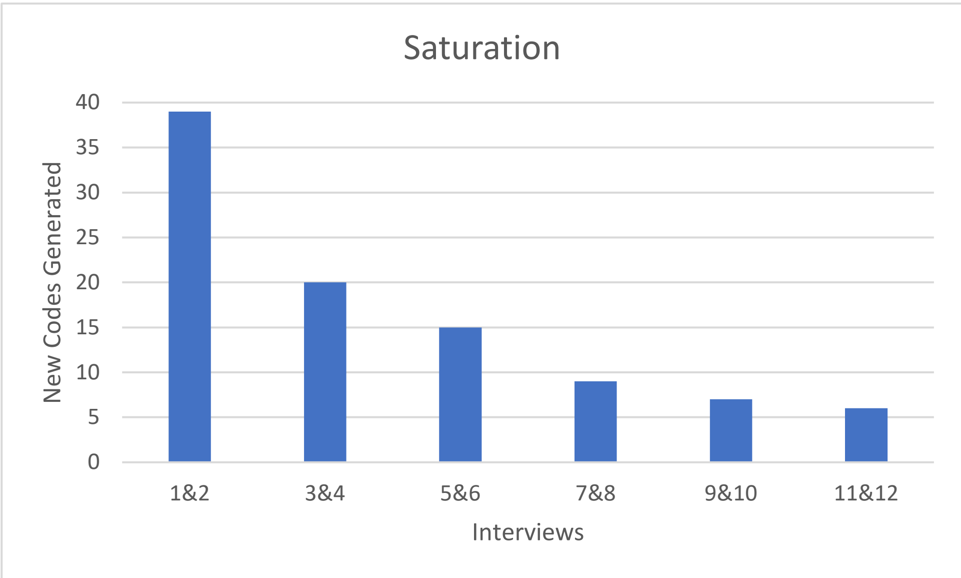

Figure 2:

New Codes Generated per Interview

As shown in Figure 2, the initial interviews (1-4) were highly exploratory, resulting in the generation of a large number of new codes as the foundational concepts of the study were established.

The rate of new code creation began to decline significantly from the fourth interview onwards, as the emerging themes started to stabilise. By the ninth and tenth interview, very few new concepts were being introduced. The final interviews served primarily to confirm and add density to the existing themes, with almost no new codes being generated.

This pattern indicates that a high degree of thematic saturation was achieved, suggesting that the data collection was sufficient to capture the main themes relevant to the research questions.

5.4 Analyses Process

Following the thematic analysis approach outlined in the research proposal, the development of the final themes was an iterative and inductive process. After the initial familiarization and transcription phase, the analysis proceeded as follows:

Initial Code Generation:

The analysis began with an initial coding process using ATLAS.ti software. Each interview transcript was reviewed, and initial codes were assigned to segments of text that captured a distinct concept or idea relevant to the research questions. This approach resulted in a comprehensive list of over 90 initial codes, see Addendum D

Sub-theme Construction:

The next phase involved clustering these initial codes based on conceptual similarity. This was an iterative process where codes were grouped and regrouped to form coherent patterns. For example, the initial codes of 'Learning driven by need', 'Motivation to learn', and 'Value linked to career journey' were grouped together because they all spoke to the core andragogical principle of relevance. This cluster was then defined as the sub-theme, ‘Making learning relevant’. This process was repeated for all initial codes, resulting in the creation of the 12 sub-themes that form the main subsections of this chapter.

Main Theme Consolidation:

In the final phase, the sub-themes themselves were consolidated. Sub-themes that addressed a shared concept were grouped together to form four overarching main themes that provide the structure for this chapter. For instance, the sub-themes of ‘Making learning relevant’, ‘Fostering learner autonomy’ and ‘Power of learner intent’ were consolidated into the main theme, AI as an enabler of andragogy.

To illustrate this analytical lineage, Table 5-2 provides a clear example of how initial codes were mapped to a sub-theme, which in turn was mapped to a main theme.

Table 5-2:

Example of the Thematic Development Process

Initial Codes	Sub-theme	Main Theme
• Need to critically question AI output • Using AI to teach critical evaluation • Proactive source curation	Questioning the LLM	The Emergence of New Core Competencies

This structured, iterative process ensured that the final themes were not predetermined but emerged directly from the participant data.

5.5 Data Collection Instruments

Before commencing data collection, two pilot interviews were conducted. Feedback from these test interviews was instrumental. It highlighted that the participants would have different levels of educational background. Thus, also varying levels of familiarity with Knowles's Andragogy and Bloom's Taxonomy. To address this a briefing was drafted and included with the interview guide, see Addendum B and Addendum C .

The briefing and interview guide were distributed to each participant prior to their interview. The briefing provided a simple overview of the two frameworks and established a common vocabulary for the discussion. The briefing also provided concise business relevant examples to illustrate each concept in a real-world context. This ensured that all participants, regardless of their background, had a foundational understanding before the interview began.

The interview guide was designed to actively facilitate understanding. This helped structure the interview for both the interviewer and interviewee. By sharing the interview guide before the interview, the interviewee was also prepared, and this enabled a rich exploration of these theoretical frameworks. The opening question in the interview guide prompted participants to describe their specific context. The variety of these contexts is illustrated by the following examples:

P12, an engineering consultant, described his approach to teaching highly theoretical concepts to industry clients:

> "So I take these very theoretical concepts, and then I try to make it, explain it in plain language. And I try to make it relevant in their world, like the second law of thermodynamics, to be able to explain to somebody who's operating furnaces."

In a different context, P10, a head of training in healthcare, detailed her team's process of converting dense policy into practical, case-based training material:

> "So I lead a team of health care workers, mostly doctors and some nurses that translate policy documents, into training material for health care workers... my team takes that clinical decision support tool and turns it into training material. So they develop cases to use that tool to make it very practical, very applicable to practice."

Similarly, P3, a research & development manager, explained his development of a more holistic training program for engineers that extends beyond purely technical skills:

> "what I've developed is a training program that will help and assist the Engineer In Trainings and facilitate the learning process in line with their job requirements. In this program, we not only discuss job requirement training, but we also discuss, I would call it streetwise training, where we teach EITs, for instance, how to manage their personal finances"

Finally, P5, a corporate AI adoption lead, described his role as being focused on teaching the practical application and strategic value of AI itself:

> "My position. I am the... AI adoption lead... And finding the best way. Of teaching someone else to use it. So that they can actually use it. And help them be better at their work."

The above quotes highlight the diverse background from the data set and the briefing and interview guide was invaluable in facilitating common understanding. Due to the nature of a semi-structured, clarifying questions were used to help participants connect their unique knowledge transfer methods, to the principles of Knowles and Bloom.

This combination of a briefing, interview guide and reflective interview questioning ensured that all participants were equipped to engage with the research questions Confirming that the data collected was consistent and based in a shared understanding of the concepts being investigated.

5.6 Theme 1: AI as an Enabler of Andragogy

The first theme that emerged from the data is that Large Language Models (LLMs) act as a powerful enabler for the core principles of adult learning as described by Knowles's Andragogy. Participants did not see AI as replacing these principles but rather as a partner to it that just enables it more effectively. This overarching theme is explored through the three sub-themes detailed below.

5.6.1 Sub-theme: Making Learning Relevant and Motivating

The interviews highlighted that LLMs empower the adult learner's need to learn. Acting as an efficient link between theory and real-world relevance, which in turn sparks the motivation to learn. Participants acknowledged the importance of relevance in motivation, as P8 stated:

> "you need to frame it in a point of reference of what is the value for the individual",

P9, a technology entrepreneur also highlighted that AI is now seen as a key tool for creating this relevance. Explained how he uses AI to understand a client's context to make his proposed solutions relevant to them:

> "I can go to ChatGPT and ask, is warehousing, where would machine vision be applicable in warehousing? And then we have a targeted way of communicating possible solutions to them."

This ability to quickly contextualize information was also highlighted by P6, an academic, who noted how AI helps her students see the practical importance of their technical work, which was previously a significant barrier to their engagement.

> "I think AI is really helping the students bridge that gap… it's allowing you to actually understand the real-life implications when it starts to simplify these concepts for you."

Furthermore, participants described how this AI-driven access to relevant information can directly trigger the motivation and curiosity to learn more. P6 described her experience using an AI mind-mapping tool to explore a new topic:

> "And then I get this quick image snapshot of something and that also gets me really excited to learn… then all of a sudden I'm in a rabbit hole and I'm so excited about this new concept."

The findings consistently indicate that AI is not just a passive information source but an active tool that helps create the conditions of relevance and motivation that are essential for adult learning to begin.

5.6.2 Sub-theme: Fostering Learner Autonomy

LLMs were also found to significantly enhance the andragogical principle of the learner's self-concept by fostering learner autonomy. Participants described how AI provides an accessible resource that reduces their dependency on human experts. Empowering them to take control of their own learning journey.

At a practical level, participants used LLMs as a tool that enables them to solve problems independently, which in turn builds confidence and motivation. P2, a process development engineer, gave a clear example of this:

> "…you can skip the part of having to ask someone who knows… you can actually solve it yourself. And I think that drives back to motivation to learn, because if you're self-driven, that's already a motivation on its own."

P8, a senior business leader, framed the AI as a readily available expert that facilitates his preferred learning style of talking and debating ideas:

> "I learn by talking and engaging with individuals… I've got a debating body at my beck and call who's an expert in everything."

P11 also emphasised that AI tools empower users to learn in a way that is personal and self-directed.

> "AI tools like ChatGPT reinforce the principles of self-directed learning…because adults can immediately explore questions in their own context and apply answers to real-world scenarios."

Perhaps the most sophisticated example was provided by P10, who described how her team uses an LLM not for answers, but as a self-directed coaching tool to deepen their own critical thinking.

> "she's telling ChatGPT to ask her questions... she's not asking it questions, she's getting, she's telling it what she's thinking... and then she's using it to ask her questions. So she's checking, she's thinking about all the different layers."

Collectively, these findings demonstrate that AI is a powerful tool for enabling a learner’s self-concept and thus promote learner autonomy. It allows individuals to control the pace, style, and depth of their own educational journey.

5.6.3 Sub-theme: The Power of Learner Intent

A sophisticated concept emerged from the interviews. It suggests that the effectiveness of AI as a learning tool is not inherent to the technology itself but is determined by the learner's own conscious intent. Participants consistently distinguished between using AI for simple Task completion vs. knowledge acquisition. Thus, AI empowers the user's pre-existing goal, whether that goal is to achieve a deep understanding or to simply produce an output.

P9, articulated intent as a key variable in his LLM-assisted learning experience:

> "…it can make this learning process shallower, or it can make it deeper. And it all depends on what the learner's objective is."

This view was supported by P5, who argued that learner investment determines knowledge transfer, and truly absorbing it:

> "You would be able to. Transfer the knowledge. Only if you are invested. In the answer. If you are not. It is like. Go on with your life. You will never remember it."

P9 further illustrated how AI can empower a user whose intent is not to learn, but to simply complete a task:

> "AI has empowered you to, to achieve things without learning. So, if that's your intent, in the past, you would have just sucked, and now you... can skip a couple of steps and still produce useful content."

P12 contrasted both types of intent, task-oriented and learning-oriented. Reinforcing that genuine, deep learning still requires a committed process that AI cannot replace.

> "if the intent was never to learn, but the intent was to solve a practical problem, which is completely valid, but if the intent is to learn, then yeah, you have to go, there's no shortcut."

These findings suggest that while AI provides unprecedented access and capability, the responsibility for genuine learning remains firmly with the human learner and is governed by their conscious intent.

5.7 Theme 2: The Transformation of Bloom's Taxonomy

The second central theme that emerged from the data is that LLMs are fundamentally transforming the process of learning as described by Bloom's Taxonomy. The findings especially indicate that AI disrupts the traditional linear progression of the framework. Participants also described how AI enables them to move quickly to the application phase with a small knowledge base and then use that experience to cement their comprehension in an iterative cycle.

5.7.1 Sub-theme: A New, Iterative Learning Process

Participants described the learning process with AI not as a one-way staircase, but as a cyclical or iterative loop. This challenges the traditional linear progression of Bloom's framework. P2, was the first to propose a re-sequenced model based on her experience:

> "...instead of it being knowledge, comprehension, application... it rather should be knowledge, application, then comprehension... And almost... it's knowledge, application, repeat. And that helps comprehension."

This concept of an Iterative learning loop was echoed by P7, a school headmaster, who noted the limitations of the traditional hierarchy in the age of AI.

> "Whereas at the moment, I think it's kind of, although it's very hierarchical in Bloom's, I think there's a lot of jumping around from layer to layer nowadays with the learning that happens and because of AI."

The need for a feedback-driven model was a recurring point. P11 argued that the framework itself needs to be updated to reflect this new reality.

> "In my view, Bloom’s model should shift from a one-way pyramid to a feedback-loop model. AI enables learners to move dynamically between levels, revisiting knowledge or comprehension as needed while testing advanced applications."

P9 provided a unique perspective by describing Bloom's as no longer a flat pyramid but a multi-dimensional object. Highlighting that an LLM allows for more fluid movement between the levels, depending on the learner's intent.

> "…it almost adds a dimension to Bloom's taxonomy in the other direction, like making it, instead of a 2D flat pyramid, it

> makes it a 3D object, where you can insert yourself at any stage, I guess."

5.7.2 Sub-theme: Adequate Foundational Knowledge

The data revealed that while participants frequently use AI to bypass or skip foundational steps for the sake of efficiency, they also hold a strong belief in the importance of foundational knowledge as a prerequisite for meaningful learning and.

P3 describe the practical reality of using AI to learn a new skill like coding, admitting that it encourages you to short circuit the traditional process:

> "…in this instance, I then basically skip the knowledge, skip the comprehension part and just prompt by asking AI to write me this code... So it short circuits, the knowledge and the comprehension part..."

However, P5, a corporate AI adoption lead, cautioned on this approach. Advocating for a fundamentals-first approach before engaging with AI for any learning endeavour:

> "I do not prefer using AI. From the get-go. To learn a topic. I would take some course. To get the fundamentals and the basics."

P12 argued that a baseline of knowledge is essential to even begin a productive interaction with an LLM:

> "…a large language model can't help ignorance. If you don't have the vocabulary to have an intelligent conversation, it will not help you."

P3 illustrated the consequence of relying on AI without this foundational knowledge:

> "…the code didn't work... And that's because I didn't have the basic knowledge and understanding, and then one of my fellow colleagues just helped me, who had the basic

> knowledge and fundamental understanding, and could solve that problem within a few minutes."

Participants agreed that foundational knowledge is essential for deep learning and for validating AI's output. However, they also admitted to using AI to bypass these same steps for the sake of efficiency. This suggests a process where a just good enough foundation is likely deemed sufficient to proceed to application.

5.7.3 Sub-theme: Shifting to Higher-Order Thinking

Participants described how AI offloads the work of remembering and understanding, freeing them to focus their time and energy on application, analysis, synthesis and evaluation. LLMs thus enable a shift in human effort towards the higher-order levels of the framework. P3 articulated this trade-off:

> "...it means that you're reducing the knowledge base, so you don't need to absorb as much knowledge. So, you actually spend more time in the application and adding value than in the memory."

P10 provided a clear example where her team uses AI to handle the lower levels, reserving the human expert for the crucial task of Analysis:

> "I think AI takes off the layers of remembering, even understanding, and it eases the weight of applying... So the analysing, we still trust a human to do."

This shift was also seen noted in advanced academic contexts. P12 explained how he encourages his PhD students to offload the manual work of writing to focus on the higher-order skills of evaluation and synthesis:

> "They need to spend more time on the higher levels of applying good judgment and evaluating and synthesis."

P6 offered a powerful synthesis of this theme, arguing that automating technical tasks like coding allows creativity to be redirected towards the user experience and human-focused design problems.

> "…ironically enough, in my opinion, I think all the AI is forcing us to focus more on the human factors... Let's look at the user interface. Let's look at what the human experience is and how can we modify that? And so the creativity goes there."

These findings demonstrate that LLMs is rebalancing the cognitive load across Bloom’s Taxonomy. The value of human intellect is seen to be shifting away from the lower levels of information recall and concentrating on the higher-order skills.

5.8 Theme 3: The Emergence of New Core Competencies

The interviews revealed a shift in what participants considered most important for learners. They explained that in a world with powerful AI, simply knowing facts is less valuable than knowing how to find, question and apply information. This led to the identification of new process skills. The most significant of these was the ability to think critically and question the AI.

5.8.1 Sub-theme: Questioning the LLM

Participants highlighted that learning with an LLM requires a shift in mindset from passive consumption to active and critical engagement. The findings indicate that learners should adopt a sceptical stance, while rigorously validating and questioning LLM-generated content. This was framed as an essential requirement for a professional in the age of AI.

P3 emphasized the importance of continuous validation:

> “…you need to do checks and balances to ensure that the output that you get is correct. You cannot just rely on AI alone.”

This was echoed by P10, who described her team’s distrusting stance and how they actively curate the sources the AI was allowed to use, controlling the process:

> “And then I choose the source documents because I've gone and found them. And then I just use it for the large language model feature of being able to synthesize. Like I'm not using it to search. I'm choosing what it looks at. I'm in charge of the input.”

This active engagement also involves a deeper level of comprehension, as P2, argued:

> "But I think what's really important as well when using AI tools is that you don't just copy and paste, but you rather understand what the provided piece of information means, even if you're not physically writing it yourself."

P8, illustrated a practical strategy for this validation, which involves cross-referencing the AI's output with trusted human expertise:

> "So, AI points me into a direction. It gets me to the answer real quickly. But I still tend to try to find industry experts who can confirm and verify."

P6 explained that learners must understand that an AI does not operate with human-like intuition and is limited by the prompts it receives:

> "when you are engaging with an AI tool, it doesn't think like a person, it doesn't fill in the gaps. So, it's only going to go off of what you put in. So, then you are able to go back and go, okay, hey, I didn't give you enough information, let me take it a step back."

Various participants echoed sentiments that questioning or either self-reflection must be formalized as a new element within learning frameworks. P3 articulated this most clearly when he was asked if he would alter Knowles's framework:

> "In this model, I don't see self-reflection... you need to self-reflect and understand it is a model and if you feed it junk, it will give you junk. I think that's a quite an important one."

This idea was also reinforced by P7, who argued that this reflective skill is crucial when interacting with LLMs, as it underpins all other cognitive abilities:

> “Oh, I think it's probably the most important thing that they're able to learn is to reflect on that. Without that reflection, they're not able to identify mistakes or errors. They're not able to incorporate any feedback that they might receive... Their critical thinking is stunted.”

P6 also argued that this evaluative step is so fundamental that it likely requires the need for a structural change to Bloom's Taxonomy:

> “I want to say almost like, you need a step of evaluation, just after knowledge, which doesn't make sense when you look at Bloom's taxonomy. “

P6 provided a practical example where a colleague’s teaching methodology shifted the focus from finding an answer to evaluating the AI's process, thereby forcing students into an inherently critical and reflective role:

> "…she came up with this idea of, instead of me giving you a question, and you must do calculations and get an answer, because everybody's tracking it through ChatGPT, your job is to design a question using ChatGPT, design a memo, and then evaluate if it's getting it wrong or right."

Together, the participants argued that critical evaluation or self-reflection are not just ancillary skills but new fundamental elements in the process of AI-assisted learning.

5.8.2 Sub-theme: Talking to the Machine

Participants identified the practical ability to interact effectively with AI as a distinct skill. This competency includes sophisticated prompt engineering and the strategic selection of the right tool for a given task. P4 stated this directly:

> "The big thing with AI… is the prompting. You need to be able to engage with it."

Participants also argued that to get a valuable response, the user must be able to articulate their needs. P5 highlighted this relationship:

> "The quality of your output. Is proportional to the quality of the prompts you give it."

This new skill also required the strategic ability to choose the right AI tool for the job. Participants noted that different LLMs have different strengths, and an effective learner must be able to discern which tool is best suited for their specific task. P6, a described this as a key step in her own workflow, deciding between different LLMs based on the specific requirements:

> "…the ability to pick the right AI tool for the job you have at hand... for literature review, I'm very quick to encourage my... students to use Google LM... It's better."

5.8.3 Sub-theme: Metacognition

A more sophisticated competency identified by several participants was the need for learners to be even more consciously aware of their own learning process, particularly the theoretical frameworks that guide it.

P9 argued that learners must now understand the theory of learning itself to avoid AI's pitfalls. He explained that while this knowledge was previously unnecessary for the learner, it has become critical in the age of AI:

> "…if you are a learner, you didn't need to know the theory of learning. But now if you are a learner, it is so helpful to know the theory of learning because… you need to make a conscious decision of for this topic. Do I want to, do I want to have a mastery of the topic? Or do I want to have a surface level understanding of the topic?"

P9 went on further to explain that this metacognitive awareness allows a learner to make a conscious decision about how to engage with AI. Without this conscious oversight, AI can disrupt the natural learning process; with it, AI can become a powerful tool for enhancement:

> "if you're not conscious about, about how it interferes with Bloom's Taxonomy… it's going to interrupt that. If you are conscious about it, it can empower it."

This perspective was reinforced by P12, who concluded that the fundamental learning frameworks remain valid, but the learner's awareness of them has become an essential new requirement for navigating an AI-augmented educational environment:

> "I don't think fundamentally these frameworks need to change. I think people need to become aware of this [the frameworks] and its relationship with AI."

5.8.4 Sub-theme: Building Transferable Skills

Participants described how AI is being used to teach process-oriented competencies, such as problem-solving and professional communication.

P5 framed it as teaching the guy how to fish, where providing a learner with a tool to solve one problem empowers them with a process they can apply to future challenges:

> “If I can use that to solve this problem. It might be applicable to this problem. That is where you are teaching the guy. How to fish."

This skill development also extended to professional presentation and communication. P1 described how he encourages his team to use AI to improve the quality of their written communication with management, viewing it as a tool for building a key professional soft skill:

> "So what the coordinators are doing currently is just to get a more professional feedback from them by using it in writing simple, like writing emails or communication to management."

This focus on transferable skills was contextualized by P12, reflecting on a broader educational shift from proactive knowledge to reactive skills suited for an uncertain future.

> "you get proactive learning, reactive learning and social learning. So proactive is you go out and you do a degree in engineering... Reactive learning is you've got a problem, you're building a Python program and you don't know how to create the CSV file. So you google it, that's reactive. In the moment you've done something that you need."

This growing emphasis on building reactive, transferable skills was framed by P7, as an essential educational strategy for an uncertain future. She argued that the core goal of teaching is now to equip learners with durable skills, as specific knowledge may quickly become obsolete.

> "we are currently teaching children for jobs that we have no idea that exist yet. So for us, it's not about the knowledge because we have no idea what we're teaching them for. But we do know that we have to teach them skills"

5.9 Theme 4: A Partner with Human-Centric Boundaries

Participants characterized LLMs not as a replacement for human intellect, but as a powerful partner with clear capabilities and equally clear limitations. This theme explores the dual nature of this partnership. It details the many ways AI serves as a powerful assistant that enhances the learning process. It also defines the boundaries where human experience, mentorship and judgment remain irreplaceable. Finally, it addresses the significant risks and dangers participants associated with the naive use of these tools.

5.9.1 Sub-theme: AI as a Powerful Assistant

Participants described LLMs as a versatile and powerful assistant, acclaiming its ability to enhance learning. The most frequently cited benefit was its role in improving efficiency by rapidly gathering, filtering and summarizing vast amounts of information. P1 described this core function:

> "And what I also like, it gives you a concentrated, the volume is less, but it's very concentrated. So, you get down to the meat of the information you want to know from."

P8 explained how he uses the conversational features of an LLM as a readily available expert to brainstorm and debate ideas, an important process to his own learning style:

> "sometimes when I'm driving, I would have a conversation. Like the conversation model of chatGPT is really impressive. And you can sort of brainstorm."

P10 described how AI can lift the creative inertia that often hinders the start of a complex writing task, providing a first draft that the human can then refine:

> "it took off that creative inertia that you have to like generate out of yourself to like start and lifted that load."

P6 explained how AI helps her students grasp complex technical concepts by translating them into understandable, real-world applications.

> "I think AI is really helping the students bridge that gap… it's allowing you to actually understand the real-life implications when it starts to simplify these concepts for you."

P4 envisioned AI's use in creating virtual simulations where learners can practice procedures in a safe, controlled environment before performing them in the real world:

> "If you were able to do that experiment, say, for instance, in a virtual AI simulation... you would have known exactly which steps to follow. Then you go into the lab and you actually do it. It will improve your safety."

5.9.2 Sub-theme: Human Experience and Expertise

In contrast to an LLMs role as a powerful assistant, participants articulated clear boundaries where they believe human experience and expertise are irreplaceable.

P11 framed AI's inability to grasp intuitive understanding gained through hands-on experience:

> "AI struggles with tacit knowledge transfer—the 'experience-based lessons' only mentors or operational exposure can provide."

P3 illustrated this gap using the simple analogy of learning to paint, arguing that no amount of theoretical knowledge from an AI can replace the physical, hands-on experience of using the tool yourself:

> "If I want to learn how to draw a picture you know, I physically need to have the paintbrush in my hand and have that physical experience and AI doesn't give that."

P1 stated that the guidance and wisdom of a mentor is a uniquely human contribution that AI cannot replicate.

> "you always learn from people as well and I think that is the one thing that AI will never take away from us because we all have mentors and I think that is the thing that AI cannot replace."

Participants reserved certain higher-order cognitive skills, such as true creativity and critical judgment, as distinctly human domains. P5 was direct in his assessment of AI's creative limits:

> "I don't think it will do any. How would you say. Groundbreaking. Creative stuff. I think it can only do. What we have already done. Much better and quicker."

5.9.3 Sub-theme: Understanding the Risks

Participants voiced significant and consistent concerns about the risks inherent in its use. A major risk acknowledged was the generation of plausible but incorrect answers. P4 used an analogy to explain how an LLM can assemble a response that is coherent but contextually flawed:

"It's almost like Scrabble. You get a whole bunch of letters and it puts an answer together of a word that makes sense. But it's not always that it's a specific word in your contex[t]."

P8 warned that this risk is systemic, potentially leading to informational echo chambers. Misinformation is amplified as LLM models begin to train on LLM-generated content.

"the LLM feeds the LLM and you just amplify the bullshit."

Another major concern was the risk of shallow understanding, where learners can generate sophisticated outputs without gaining real competence, creating an illusion of competence. P4 described this gap: :

"as soon as you throw someone into a pool to actually do it, then they have no idea because they've never done it before."

P4 cited an external study to emphasize his concern that offloading cognitive effort to AI can lead to diminished human intellectual engagement:

"I think I've read... that MIT paper... You only use 47% of your brain when you engage with AI... because... They reduce the knowledge base."

This leads to a longer-term fear of skill atrophy and the risk of losing human intuition. P8 worried that over-reliance on standardised AI outputs would erode competitive advantage of a company:

But the competitive advantage comes in with this company A might have, what do you call it, intuitive knowledge from their employees that company B does not have. And I'm very scared that we're going to lose that intuitiveness

5.10 Chapter Summary

It was demonstrated that LLMs act as powerful enablers of Knowles's Andragogy, informing the first research question. It was also shown that LLMs transform Bloom's Taxonomy from a linear model into a more dynamic and iterative process, informing the second research question.

The analysis then went further to identify two additional themes that further contributed to enriching the context for the two research questions. These include, identifying competencies required to navigate this new landscape and LLMs role as a partner that enhances learning, with human-centric limitations and inherent risks that must be managed.

Chapter 6:
Discussion

6.1 Introduction

This study was designed to explore how LLMs affect the applicability of two cornerstone frameworks in adult learning, Knowles's Andragogical principles and Bloom's Taxonomy. The research was guided by two central questions:

1. How do LLMs affect Knowles's Andragogical principles within the context of corporate or institutional knowledge transfer?

2. How do LLMs affect Bloom's Taxonomy within the context of corporate or institutional knowledge transfer?

The thematic analysis presented in Chapter 5 distilled the rich data from the interviews into four central themes. This chapter now moves from the presentation of these findings to their interpretation and discussion. Each theme and its sub-themes from Chapter 5 will be analysed through the lens of the research questions and the broader academic literature unpacked in Chapter 2. It will aim to understand to what extend the findings confirm or challenge current literature.

6.2 Research Question 1:

The first research question sought to understand how Large Language Models (LLMs) were affecting the principles of Knowles's Andragogy within a corporate or institutional context.

The findings presented in Chapter 5 under the theme 'AI as an enabler of andragogy' suggested that LLMs did not replace these principles but rather acted as powerful accelerators. It argued that LLMs enabled andragogy but also introduced a critical new condition for its effective application.

6.2.1 The Acceleration of Relevance

Knowles et al. (2014) suggested that adults are most motivated when they understand the why, what and how of what they are learning and can see its immediate application to their real-life situations and problems. Their motivation is primarily driven by internal factors like personal growth, satisfaction and career payoff Knowles et al. (2014).

Participants in this study confirmed this, explaining that LLMs served as a powerful tool for bridging the gap between abstract concepts and real-world application. One participant particularly noted that the value of any learning must be framed for the individual.

This aligns with literature that identified that LLMs offered real-time feedback and simplified complex topics (Cribben & Zeinali, 2023; Gonsalves, 2024), thereby creating adaptive learning experiences (Hmoud & Ali, 2024).

Traditional methods relied on an instructor to provide context, however LLMs transformed the learning process from a passive reception of information into a learner-driven dialogue. As Valcea et al. (2024) observed, learners actively shaped their educational journey by prompting the AI for practical examples. They even adjusted the complexity of explanations to suit their needs, a level of interactivity not previously possible.

This capability to forge immediate connections between theory and practice allowed learners to bypass the potential disengagement that arose from intangible learning (Yusuf et al., 2024). One participant captured this dynamic, by describing how getting a quick snapshot of relevant information made her really excited to learn and sent her down a rabbit hole of self-directed exploration.

This research showed that by making knowledge immediately applicable, LLMs efficiently promoted the adult learner’s orientation to learning (Knowles et al., 2014). It showed that LLMs served as a powerful catalyst to initiate the learning process for professionals who might otherwise be disengaged from material they perceived as irrelevant.

6.2.2 The Empowerment of Autonomy

Knowles's second principle theorised that as individuals matured, their self-concept moved from a form of dependency to a self-directed individual (Knowles et al., 2014). The findings from Chapter 5 indicated that LLMs empowered this self-concept by fostering learner autonomy.

Participants described LLMs as a debating body at your beck and call. It was also referred to as method to solve a problem by yourself, which reduced the reliance on the availability of a human expert. This enabled learner to take control of their own learning journey. This aligned with Adarkwah’s (2024) view that LLM offered a unique opportunity to personalise learning experiences and foster independence.

Moreover, LLMs were also increasingly positioned as personalised support assistants that augmented or even replaced support traditionally provided by peers and instructors (George et al., 2025). Studies also noted that LLMs acted as a support anchor or a virtual tutor outside of scheduled office hours, which provided instant feedback that saved time for both students and educators (Cribben & Zeinali, 2023; George et al., 2025).

Research even showed that LLMs produced learning gains equivalent to those from human tutors, especially in environments where learners studied alone (Pardos & Bhandari, 2024). A real-world example of this shift was the experience of participant P2, who celebrated the ability to not have to ask for outside help.

The concept of the extended mind (Clark & Chalmers, 1998) and connectivism (Siemens, 2005) offered an alternative interpretation. Considering their perspective, an LLM is not merely an external tool consulted by the learner, it became an integrated part of the learner's cognitive process itself, constantly and reliably available to guide the learner's actions.

The participants in this study described their relationship with LLMs in a strikingly similar manner. When P8 referred to the LLM as a debating body at your beck and call, he described an intelligent node in a network as a cognitive partner that was as integral to his thought process.

A sophisticated demonstration of this principle was offered by P10. She described her manager using an LLM not for answers, but as a self-directed coaching tool to develop her own understanding by prompting it to ask her questions. A clear example of an autonomous learner leveraging an LLM. This integration between LLM and learner allowed them to pursue their own lines of inquiry. It also allowed them to test ideas in a manner that was perfectly aligned with the automated nature of the adult learner as described by Knowles.

This was also reinforced by P11, who highlighted that a LLM tools allowed adults to explore questions in their own context, immediately. An LLM thus transformed the learner's environment into an interactive cognitive space that the learner shaped according to their needs and goals.

6.2.3 The Critical Role of Learner Intent

The findings highlighted a nuance that emerged from the interviews. The educational value of an LLM was determined not by the technology itself, but by the learner's conscious intent.

These findings echoed Holton's claim that context and purpose ultimately decided the quality of adult learning (Holton et al., 2001). Though, the conditionality of this context and purpose 'layer' in the revised andragogical model was never specified, it was seen as just a contextual guidance.

Participants however, consistently argued for this conditionality, distinguishing between using a LLM for knowledge acquisition versus simply, task completion. One participant stated that AI can either make the learning process shallower, or it can make it deeper. The participant argued that it depended on the learner's objective.

This provided a clear psychological mechanism for the expertise paradox identified by Valcea et al. (2024). It theorised that AI's efficiency in lower-level tasks weakened a student's development of higher-level thinking. The learner's intent to simply complete a task, directly lead to deskilling and superficial learning (Gonsalves, 2024; Valcea et al., 2024).

A study by Atanassova & Cabori (n.d.) also captured this relationship. Their research showed that outcomes improved only when learners used AI purposefully. When AI was used casually, reasoning weakened and collaboration suffered. They concluded that the technology empowered or impaired depending on how intentionally it is woven into the learning process. As participant P5 observed, knowledge transfer only occurred when you were invested in the answer, otherwise, the information was fleeting and never truly learned.

This view was again emphasised by Valcea et al. (2024), who reasoned that the learners must only leverage AI to augment their skill development rather than foster overreliance. The core principle was that the learner's intent dictated the outcome.

Other participants added further context and argued that when learners knew the theory of learning, it also helped them make more informed decisions during LLM engagement. This metacognitive oversight, also either eased or sabotaged Knowles Andragogical principles.

These distinctions introduced a critical new condition to andragogical theory. It was no longer enough for an adult learner to be only motivated. Learners were also required to possess the metacognitive skill to distinguish between the goal of solving the problem and the goal of learning from the process of solving it.

6.3 Discussion in Relation to Research Question 2:

The second research question examined the impact of LLMs on the established hierarchical framework of Bloom's Taxonomy. This taxonomy has served as a foundational tool for structuring and evaluating cognitive milestones, based on the linear progression from lower-order thinking skills to higher-order ones (Anderson & Krathwohl, 2001; Bloom, 1956).

The findings from Chapter 5, particularly under the theme ‘The transformation of Bloom's Taxonomy’, indicated that LLMs were not merely another tool to be added onto the existing hierarchy. Instead, it was viewed as a disruptive force that transformed Bloom’s learning process.

6.3.1 From Linear Hierarchy to an Iterative Process

The most significant disruption to Bloom's Taxonomy identified by participants was the breakdown of its linear, sequential structure. The traditional model assumed that mastery of each level was a prerequisite for advancing to the next. It argued one must remember and understand before one can effectively apply or analyse (Anderson & Krathwohl, 2001).

However, participants consistently described their learning process with AI not as a one-way staircase but as an iterative feedback loop. P2, for instance, proposed a inverted iterative model that was first knowledge, application, then comprehension and then repeat. This sentiment was echoed by P7 who also noted that LLMs allowed the learner to jump around between the layers.

This finding provided strong empirical support for recent scholarly arguments that AI challenged the rigidity of Bloom's framework. Gonsalves (2024) observed that learners moved fluidly between cognitive stages in a recursive, non-linear manner. Concluding that this dynamic disrupted the linearity of Bloom's model. Jain & Samuel (2025) observed the same process and added an ancillary step to Bloom's model, referred to as ‘iterative learning’.

Similarly, Elim (2024) proposed a cognitive model for AI use where the stages of questioning, feedback and reflection repeated in a loop until students were satisfied. The lived experiences of the experts in this study confirmed these theoretical propositions. It demonstrated that in practice, learners no longer ascended a fixed pyramid. However, they were navigating what P9 described as a 3D object, which allowed for more fluid movement between levels.

The mechanism that enabled this iterative process can be given further context by the extended mind theory connectivism. The rapid feedback loop created by the LMM functioned as an external cognitive partner in an active network (Clark & Chalmers, 1998; Siemens, 2005). When a learner attempted to apply a concept with only a minimal foundation of knowledge, they received immediate feedback and used that applied experience to circle back and deepen their understanding. This iterative cycle was a validating or rather epistemic action where an external tool and network was used to augment cognitive processes. This is arguably far more efficient than traditional methods that required you to have waited for human feedback or be engaged in extensive trial and error.

There were several proposed revisions of the taxonomy, including Churches (2010) Digital Taxonomy, which mapped digital activities onto the existing levels. More recently, Hmoud & Ali's (2024) AIEd Bloom's Taxonomy merely relabelled the stages to reflect interactions with AI. However, these adaptations largely retained the original linear, hierarchical structure. While these models proposed adaptions for technology-enhanced learning, the participants in this study suggested a more fundamental structural shift.

It is not just the activities within the levels that changed, but the sequence of progression between them. As Gonsalves (2024) found, learning with AI involved iterative questioning and refinement, where students actively merged comprehension with higher-order thinking. This fostered a more adaptive and potentially deeper cognitive engagement than what a traditional Bloom's model allowed.

6.3.2 The Paradox of Adequate Foundational Knowledge

The findings also revealed a significant challenge to the acquisition of foundational knowledge, which underpinned Bloom's Taxonomy's. Participants frequently described using LLMs to bypass or short circuit the remember and understanding stages. At the same time participants held a strong belief in the importance of knowledge acquisition for meaningful learning.

This created a paradox where the LLMs efficiency conflicted with the perceived importance of the knowledge acquisition stage. This highlighted a weakness in the taxonomy that necessitated a new guiding mechanism.

To understand what is being bypassed, it's useful to employ the revised Blooms taxonomy proposed by (Anderson & Krathwohl, 2001). It dissected each stage of Blooms into factual, conceptual and procedural knowledge.

Anderson & Krathwohl (2001) implied that learners build competence by layering these knowledge types. However, LLMs disrupted this layering. This was illustrated by P3, who admitted using LLMs to skip the knowledge and comprehension steps when learning to code.

Through the lens of Anderson & Krathwohl, the learner obtained a functional output without necessarily acquiring the underlying factual knowledge (code syntax rules), conceptual knowledge (understanding programming logic) or procedural knowledge (the steps to write and debug code independently).

This shortcutting risked creating an illusion of competence (Valcea et al., 2024). Learners generated sophisticated outputs that concealed deficiencies in factual recall, conceptual understanding or procedural fluency (Anderson & Krathwohl, 2001). This also aligned with concerns about superficial learning (Gonsalves, 2024).

The failure P3 experienced when unable to debug LLM-generated code illustrated the consequences of these knowledge gaps. As P12 emphasized, a large language model cannot help inherent ignorance. Thus, it cannot substitute for a lack of foundational factual, conceptual or procedural understanding.

Ultimately, this paradox returned the focus to the learner's role and their conscious intent, a theme discussed in the context of andragogy in section 6.2.3. The LLM presented a choice, to either engage in the process of building a robust foundation or to accept a superficial foundation for the sake of efficiency.

Therefore, the inherent risk, is not with the technology itself, but with the learner’s uncritical use of it. This established the clear need a mechanism that prompted learners to question and reflect and consciously manage the paradox.

6.3.3 Shifting Human Effort to Higher-Order Thinking

LLMs enabled a significant shift in human effort toward the higher-order levels of the framework. Participants consistently described a process of offloading the work of remembering and understanding to an LLM, which freed their cognitive resources to focus on apply, analyse, evaluate and create.

P3 described this shift, indicating that when you don't need to absorb as much knowledge, you actually spent more time in the application phase and adding value. This aligned with the conceptual argument made by Ng et al. (2021), who predicted that lower-order tasks would likely be offloaded to an LLM. This allowed learners to concentrate their effort on critical engagement, integration and reflection.

The experiences of the participants in this study also provided empirical validation for this prediction. P10, a Head of Training in healthcare, offered a professional example. Explaining that her team now used an LLM to remove the layers of remembering and understanding and reserved the human expert for the crucial task of analysing. This practical application in a demanding field highlights the perceived reliability of AI for foundational tasks and the recognition of where human intelligence still provides superior value.

This mirrored Huang & Rust’s (2018) findings, which indicated that AI first replaced tasks requiring mechanical and analytical intelligence. This led to a shift in the importance of human skills toward intuitive and empathetic intelligence. Participant P12 explicitly endorsed this shift in his approach, he encouraged his PhD students to offload the manual work of writing and to focus on the higher levels, applying good judgment, evaluating and synthesis.

Furthermore, the offloading of lower-order stages can also be analysed as an application of the extended mind theory (Clark & Chalmers, 1998) and connectivism (Siemens, 2005). Through this lens the LLM is again not just a passive repository of facts but an active node in a network and a component of the cognitive system, which remembered and performed lower-level processes on behalf of the user. This freed up the user's resources to be allocated to more complex and creative tasks. As P6 insightfully concluded, by automating technical work, LLMs forced us to focus more on the human factors. This redirected human creativity toward user experience and human-centric design problems.

Ultimately, LLMs fundamentally transformed the nature of knowledge transfer in adult learning. Instead of focusing on transmitting foundational factual and conceptual knowledge, the emphasis shifted towards transferring and cultivating the uniquely human skills of critical judgment and innovation, which was needed to effectively utilise the LLM-provided foundation.

6.4 The Integration of Learning Framework and Essential Competencies

The preceding analysis demonstrated that LLMs both enabled and disrupted established learning theories. The discussions of Knowles's Andragogy and Bloom's Taxonomy have revealed a shift towards more dynamic, iterative, and learner-driven processes.

This final section unpacks participants findings related to new core competencies that learners required in an LLM environment. It was also argued that some of these competencies were so vital that they should be integrated in the frameworks themselves. The powerful capabilities that participants highlighted in AI was also contrasted against the unique role that the human mentor still needs to play.

6.4.1 New emergent competencies and the Critical Questioning Layer

Participants consistently argued that effective learning with AI required a fundamental shift from passive consumption to actively and critically engaging the content. This was echoed by P10 and P8 who both adopted a sceptical or distrusting stance and rigorously validated LLM-generated content by cross-referencing with trusted human expertise.

This practical need for continuous validation aligned strongly with academic literature highlighting concerns about LLM accuracy (Pardos & Bhandari, 2024) and LLM bias (Selwyn, 2024). It also provided empirical support for frameworks that explicitly included evaluation when interacting with LLM-generated texts (Yusuf et al., 2024).

Crucially, participants themselves advocated for this structural change and highlighted it as a distinct step. P3, for instance, identified the absence of self-reflection in traditional models as a critical gap for the AI era. P6 also suggested the need for a step of evaluation, just after knowledge and challenged the traditional sequence. P7 reinforced this and called reflection the most important thing learners need, without which critical thinking is stunted.

This participant feedback suggested that analyse and evaluate, traditionally positioned as the summative stages of Blooms, were insufficient in the AI context. Instead, it highlighted the need for a distinct questioning phase that functioned as a layer throughout the process, from initial information discovery to final creation. Thus, it functioned continuously rather than sequentially.

The distinct nature of this questioning layer was further evident in its focus. Traditional analyse and evaluate stages primarily assessed the final content or product (Anderson & Krathwohl, 2001). Whereas the participant's proposed questioning layer questioned how the AI assembled and applied factual, conceptual, and procedural knowledge throughout various points in the learning loop.

This new questioning layer was enabled by two emergent competencies. The first was prompt engineering, which P4 referred to as knowing how to talk to the machine and aligned with the 'use and apply' dimension of AI literacy (Ng et al., 2021). The more critical competency is metacognition, the learner's awareness of their own intent and learning goals, which provided the strategic direction for questioning. P9 also argued that when learners knew the theory of learning they could make a more informed decision about how to engage with an LLM.

This elevated metacognitive knowledge (Anderson & Krathwohl, 2001) from a supplementary aspect to a directive skill. Crucial for mitigating the risks of shallow understanding and the illusion of competence highlighted by Valcea et al. (2024).

Ultimately, the findings indicated that learners can no longer be passive recipients of information but must become active directors of their cognitive partnership with AI. A revised model must therefore incorporate a metacognitive questioning layer of critical evaluation and self-reflection. The prominence of learner intent in effectively managing this layer provided a direct link to the new andragogical condition proposed in section 6.2.3, setting the stage for the integrated framework to be developed.

6.4.2 Defining the LLM as a Partner with Human-Centric Boundaries

Overwhelmingly, participants described LLMs as versatile and powerful assistants that enhanced knowledge transfer. A primary benefit highlighted was efficiency, particularly in filtering and summarising vast amounts of information. P1 argued that LLMs helped learners get down to the meat of the required knowledge.

Beyond mere information retrieval, participants valued the LLM as an active sparring partner or sounding board, to aid their thinking processes. Participant P8 described leveraging the LLM's conversational features as a readily available expert to brainstorm and debate ideas. Cribben & Zeinali (2023) and Gonsalves (2024) specifically noted an LLM's ability to promote understanding and application by breaking down difficult topics into understandable insights.

LLM was also recognised as a practical instructional aid. P4 envisioned leveraging this capability further through AI-driven simulations where learners practiced procedures safely before any real-world application. This aligned well with the proposed AIEd models that incorporated simulation for experiential learning (Hmoud & Ali, 2024).

Participants also identified LLMs as a tool for overcoming creative blocks. P10 highlighted how AI can lift the creative inertia often encountered at the start of difficult writing tasks, as it provided a first draft which was then refined by a human. While some participants questioned the novelty of AI-generated creativity, its utility as a brainstorming tool or starting point was clearly valued which aligned with applications mentioned by Yusuf et al. (2024).

In contrast to the LLM's role as a powerful assistant, participants indicated where they believed human experience and expertise remained irreplaceable. The participants agreed that an LLM processed and synthesised vast amounts of explicit knowledge efficiently. They however argued that it lacked the capacity for the nuanced understanding derived from lived human experience.

Participant P11, framed this as a major gap, in his experience an LLM struggled with experience-based lessons which operational exposure provided. Participant P3 vividly illustrated this using the analogy of learning to paint, he argued that no amount of theoretical instruction from an AI was able to substitute for the physical experience of actually holding the brush. This distinction aligned with learning theories that emphasised the experiential and social learning at the start of Chapter 2.

This experiential gap was extended to the concepts of mentorship and empathy. Participant P1 for instance, reasoned that the guidance and wisdom of a mentor was something a LLM would never be able to take away. This resonated again strongly with the framework proposed by (Huang & Rust, 2018), which identified empathetic intelligence (the ability to recognise, understand and respond appropriately to human emotions) as the most difficult level for an LLM to replicate.

Participants reserved certain higher-order cognitive skills, particularly creativity as distinctly human domains. Participant P5 was direct in his assessment of AI's creative limits. Stating that he did not think an LLM it would do any groundbreaking or creative stuff. Arguing that it was only able to do what we have already done only much better and quicker.

This view supported critiques that suggested that generative AI excelled in synthesis with existing patterns but fell short of genuine creativity. It also aligned with concerns raised by participants and literature about the innovation paradox where reliance on an LLM homogenised creative outputs and inhibited originality (Valcea et al., 2024).

The analyses indicated that far from being rendered obsolete, the human role in corporate knowledge transfer became more focused at transferring context-specific wisdom and judgment (Gonsalves, 2024).

6.5 Chapter Summary

This chapter has provided a detailed interpretation of the study's findings. Analysing it through the lens of existing literature. The discussion demonstrated that LLMs have not rendered these frameworks obsolete. Instead LLMs acted as catalysts that both enabled and transformed them.

In response to the first research question, the analysis revealed that LLMs act as enablers to Knowles's andragogical principles. They accelerated the adult learner's knowledge transfer by providing instant relevance, which in turn sparked intrinsic motivation. It also further empowered learner autonomy by functioning as an integrated cognitive partner.

However, it was found that in an LLM augmented environment, Knowles’s Andragogy was conditional, depended upon the learner's intent. The ability of an adult learner to separate task completion from genuine knowledge acquisition introduced a new layer to andragogy. This in turn required the learner to have metacognitive awareness about their goals and purpose.

The analyses also highlighted a transformation of Bloom's Taxonomy. The findings suggested that the traditional, linear hierarchy of cognitive skills is being replaced by an iterative feedback loop. This allowed learners to move fluidly between lower and higher-order thinking.

The disruption of Bloom’s also created a paradox around foundational knowledge. In LLM augmented environments learners were tempted to short circuit the basic cognitive tasks for the sake of efficiency, even though they acknowledged its importance. This facilitated a process where human cognitive effort was shifted away from lower-order tasks toward higher-order tasks.

Emergent roles of both the learner and the LLM in was also analysed. To navigate this transformed environment, learners cultivated a set of metacognitive competencies. These included critical evaluation, validation and self-reflection, supported by skills such as prompt engineering.

The LLM, in turn, despite its strengths was deemed a powerful assistant for information processing. It was seen as increasingly important for a human to navigate inherent risks in an organisational context.

These insights provided the foundation for the final chapter, which will present the study's conclusions and offer recommendations for organizations and adult learners seeking to harness the potential of LLMs effectively for knowledge transfer.

Chapter 7:
Conclusions and Recommendations

7.1 Introduction

The final chapter synthesises the study's thematic findings which was presented in Chapter 5 and analysed it against existing literature in Chapter 6. The aim is to provide a conclusion in response to the guiding research questions. It will also discuss the conceptual factors that arose from the study and present them to inform the framework for adult learning in LLM augmented learning environment

This chapter will also outline the theoretical and practical implications of the findings and offer recommendations for organisations and adult learners and trainers educators.

7.2 Principal Findings

7.2.1 RQ1: How do LLMs affect Knowles's Andragogical principles within the context of corporate or institutional knowledge transfer?

The findings indicated that LLMs interacted with Knowles's principles in a complex manner(Knowles et al., 2014). It acted as a potential enabler for knowledge transfer, but only with the introduction a critical new condition.

From the data it was gather that LLMs was perceived to enhance the Knowles' principles of 'need to know' and 'orientation to learning' by providing almost immediate relevance. Efficiently linking abstract concepts and practical application (Cribben & Zeinali, 2023; Gonsalves, 2024)

This capability in turn intrinsically sparked Knowles' other principle 'motivation to learn'. It allowed learners to instantly connect theory to their specific challenges and in turn fostered self-directed exploration. Thus, the 'self-concept of the learner' principle was also bolstered by promoting autonomy and self-direction (Knowles et al., 2014).

Because it functioned as an accessible, on-demand cognitive partner or virtual tutor (George et al., 2025; Pardos & Bhandari, 2024), it was found that LLMs reduced reliance on human experts and empowered individuals to control their learning journey. This aligned with the theory of connectivism and extended mind, as the LLM became an integrated part of the learner's network and cognitive process (Clark & Chalmers, 1998; Siemens, 2005).

The study also revealed that LLMs severed the assumed link within andragogy between the motivation to solve a real-life problem and the cognitive effort required for learning during that process. This introduced the learner's conscious intent as a critical influencing factor. Participants consistently distinguished between using an LLM for genuine learning versus merely completing a task. Therefore, the findings suggested that in the presence of an LLM, the enabling potential of Knowles's principles is conditional upon the learner's metacognitive awareness and deliberate intent to learn.

Without this intent the to learn, the efficiency offered by an LLM risked shallow engagement from the learner and ultimately deskilling the learner (George et al., 2025; Gonsalves, 2024; Valcea et al., 2024). However, with the intent to learn, LLMs became a powerful tool for accelerating self-directed as envisioned by Knowles, see Table 7-1 below.

Table 7-1:

Andragogy Principles + Intent

Knowles's Principle	**Condition**	**How LLM Enables and Accelerates It**
The Need to Know	**+ Intent**	LLMs provide immediate, on-demand relevance (Knowles et al., 2014). A learner can ask how a concept applies to their specific problem and receive a contextualized response (Cribben & Zeinali, 2023; Yusuf et al., 2024), sparking motivation.
Self-Concept	**+ Intent**	LLMs empower learner autonomy by acting as an ever-present, self-directed tool (Knowles et al., 2014). It functions as a readily available "debating body", reducing reliance on human expert availability (Adarkwah, 2024; George et al., 2025).
Learner's Experience	**+ Intent**	The learner's prior experience (Knowles et al., 2014) becomes the critical lens through which they (a) craft effective prompts and (b) evaluate the AI's output. The LLM can act as a "sparring partner" for their existing mental models.
Readiness to Learn	**+ Intent**	The LLM aligns perfectly with a real-world, problem-based readiness (Knowles et al., 2014). The learning is no longer abstract theory but is applied directly to a challenge the learner is facing at that moment.

Orientation to Learning	**+ Intent**	The AI facilitates a problem-centered, rather than content-centered, approach (Knowles et al., 2014). It allows learners to bypass purely theoretical instruction and immediately connect concepts to practical application and real-world scenarios.
Motivation to Learn	**+ Intent**	By providing instant, useful feedback and simplifying complex topics (Gonsalves, 2024; Hmoud & Ali, 2024), the LLM can make learning feel less daunting and more exciting, potentially igniting internal motivation and deeper, self-directed exploration.

7.2.2 RQ2: How do LLMs affect Bloom's Taxonomy within the context of corporate or institutional knowledge transfer?

The findings demonstrate that LLMs also transformed Bloom's traditional linear hierarchy (Anderson & Krathwohl, 2001; Bloom, 1956) Instead of a sequential progression, learning with an LLM adopted an iterative feedback loop.

The participants and research indicated that learners applied concepts with minimal remembering or understanding and used the LLM's immediate feedback to refine their approach and then cycled back to deepen comprehension. The learners effectively jumped in between levels in a non-linear fashion (Elim, 2024; Gonsalves, 2024). This process was facilitated by the LLM functioning as an external cognitive partner in a network, consistent with the extended mind theory and connectivism (Clark & Chalmers, 1998; Siemens, 2005).

This disruption gave rise to a paradox. LLMs enabled users to bypass the lower-order stages of remembering and understanding due to its efficiency at these tasks. (Anderson & Krathwohl, 2001). Simultaneously, participants stressed the importance of mastering the lower order stages to be able to validate LLM outputs, which in turn enabled higher-order thinking. This paradox will only be successfully managed by avoiding superficial understanding, alternatively, this would lead to an illusion of competence (Gonsalves, 2024; Valcea et al., 2024). Conceptually this paradox was depended on the learner's conscious intent (discussed under RQ1) and the application of continuous evaluation.

Nevertheless, by offloading tasks associated with remembering and understanding, participants acknowledged that AI freed up cognitive resources. Which in turn allowed learners to focus on the human learner's strengths (Ng et al., 2021).

However, leveraging this offloaded capacity was still dependant on critical evaluation and the intent of the learner,

Integrating these points, the study findings suggested the emergence of a persistent questioning layer as a crucial mechanism in an LLM enabled learning environment. As highlighted by participants, this involved applying critical evaluation, validation, and self-reflection throughout the iterative loop, not just as a final step (Yusuf et al., 2024).

See Figure 3 for a visual representation. From this study, students can enter the iterative blooms model at any stage and iterate in either direction. Movement from one stage to the other is informed by the proposed questioning layer.

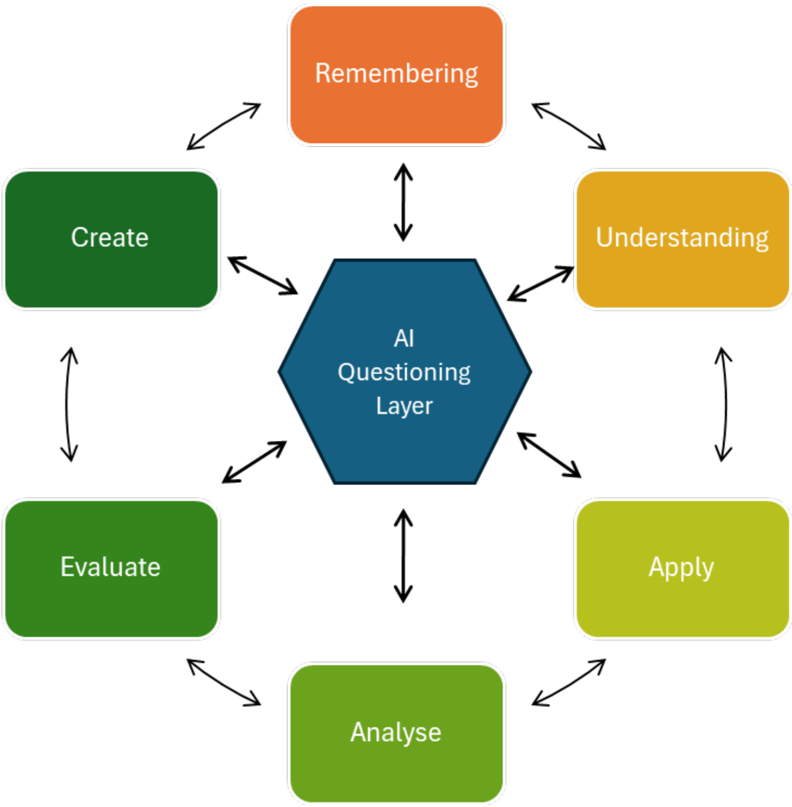

Figure 3:

Iterative Blooms with Questioning layer

This questioning layer becomes essential for navigating the paradox discussed above. Rather than simply generating outputs without deep learning it enables the use of cognitive offloading towards genuine higher-order thinking. This model functions continuously rather than sequentially, challenging the traditional placement of evaluation solely at the upper end of Bloom's hierarchy.

7.3 Synthesizing the Findings

7.3.1 Linking Andragogy, Taxonomy, and Emergent Competencies

The preceding analysis highlighted distinct impacts of LLMs on Knowles's Andragogy and Bloom's Taxonomy. However, the analyses in Chapter 6 revealed interconnections between these findings.

The conditional nature of learner intent can be found to have a direct parallel in the proposed iterative Bloom's Taxonomy. This intent serves as a metacognitive switch that informs both models. It determines if the learner approaches the interaction with the goal of genuine learning or simply task completion.

When the intent is to learn it accelerates Knowles' principles. The learner then operates as a motivated and self-directed individual actively seeking understanding. It can then also be argued that this intentional andragogical stance directly informs the application of the questioning layer. A self-directed learner, driven by intrinsic motivation is precisely the individual who will engage in the necessary critical actions expressed by this layer. On the other hand, a passive learner simply seeking an output would not.

Therefore, learner intent informs the newly identified actions or competencies. This includes continuous critical evaluation, validation and self-reflection, which could be considered the practical application of the questioning layer.

7.3.2 New integrated framework

This link identified in 7.3.1 highlighted that the same metacognitive awareness will inform both Knowles' and Bloom's framework. It will thus be increasingly important to manage both the conditional nature of andragogy and the potentially superficial nature of the proposed taxonomy.

This leads to the proposal of a conceptual model that combines both Knowles' Andragogy and Blooms Taxonomy, informed by the intentional and questioning layer, Figure 4. This proposed combined framework could inform knowledge transfer in a world where LLMs will have an ever-increasing impact.

Note that the proposed Bloom's framework in Figure 3 was condensed to illustrate the combined framework in Figure 4.

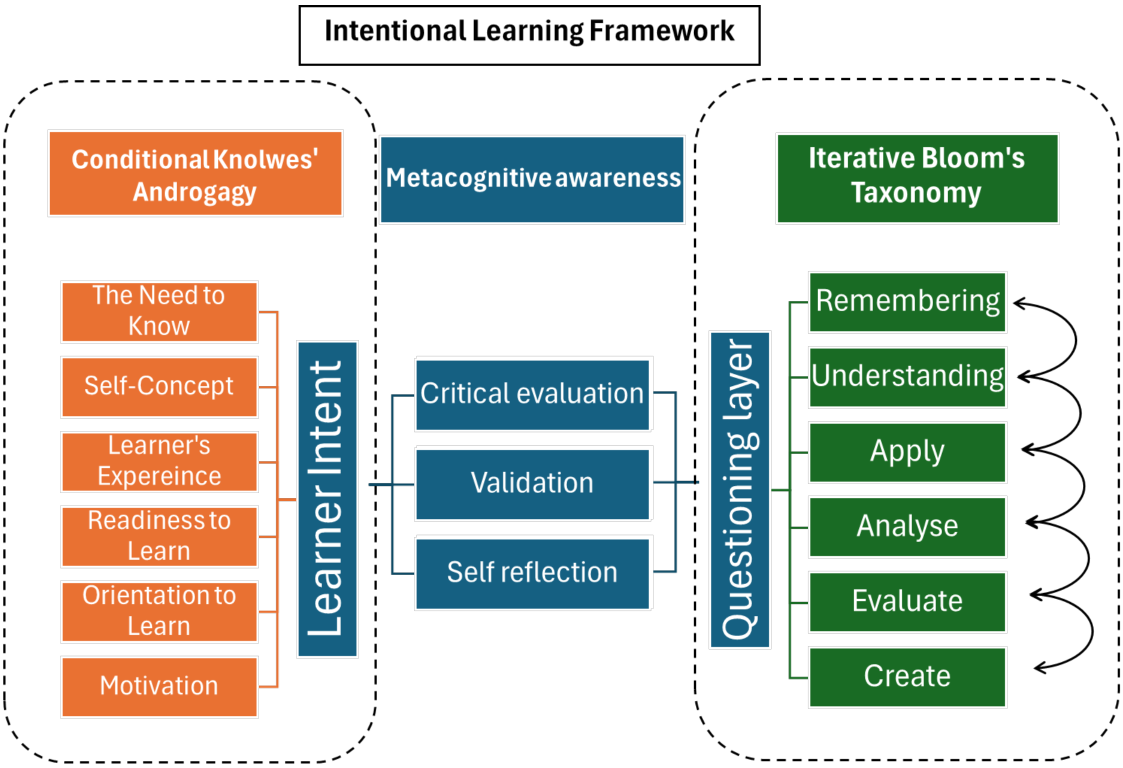

Figure 4:

Intention Learning Framework

In this framework, learners must consciously decide whether their goal is a more efficient method of task completion or building genuine understanding. Without this conscious oversight, the efficiency offered by LLMs can undermine both the learning principles of Knowles and Bloom.

An adult learner could be required to complete an unfamiliar task. If the learner identifies that learning this skill is not relevant, the learner is then able to use the LLM to provide the necessary knowledge. The LLM allows the learner to enter the iterative blooms model at the apply stage. Since the intent is not to learn, the learner will also not be obliged through self-reflection to iterate up or down to further knowledge acquisition.

Conversely, a learner with an intent to learn, activates the intent condition of the framework and will be a motivated and self-directed learner. This learner will enter the iterative Bloom's framework dependant on the learner's preference. The learner will then proceed to iterate in any direction in Bloom's framework. Informed by the learner's critical evaluation, validation and self-reflection of the LLMs output dependant on the learner's intent.

This proposed framework emphasises a redefined role for the adult learner in an LLM-augmented environment. Skills like prompt engineering become essential tools to engage with the new proposed framework.

7.4 Contribution of the Study

This study provided an empirical adaptation of Bloom's Taxonomy for LLM-augmented contexts. It moved beyond the traditional linear hierarchy and proposed an iterative loop model, supported by research (Elim, 2024; Gonsalves, 2024).

The research expanded upon Knowles's Andragogy by identifying learner intent as a conditional step for effective LLM-assisted learning. It highlighted how a LLM can decouple the act of task completion from the process of learning, a distinction not prominent before the advent of powerful generative tools (Valcea et al., 2024).

The research also conceptualised a questioning layer as a distinct and continuous mechanism for navigating LLM output. It was suggested as a necessary structural addition to cognitive process model, aiming to ensure learner engagement (Yusuf et al., 2024)

The study’s main contribution lies in providing a conceptual link between Knowles’ Andragogy and Bloom’s Taxonomy. No formal framework like this was found to be present in literature. The research goes further to explain how the framework should be navigated in an LLM-augmented environment.

The broader findings from the study further complement this proposed combined framework by informing where human judgment remain essential. Highlighting the need to develop these human capabilities alongside AI literacy

7.5 Recommendations

7.5.1 Recommendations for Corporations and Institutions

Organisations and educators should explicitly adopt and teach the proposed framework in Figure 4 as a core component of digital literacy. Training must however be focused on the role of learner’s intent. Equipping individuals to consciously determine whether their goal is deep understanding or efficient task completion before and during LLM engagement.

As LLMs increasingly automate lower-order cognitive tasks (Ng et al., 2021) human competitive advantage also shifts upward. Therefore, investment in professional development must prioritise uniquely human skills. This includes fostering mentorship programs for tacit knowledge transfer. Which in turn will enhance critical evaluation and validation skills. Self-reflection practices should also be encouraged, prompting learners to assess their own understanding and the LLMs limitations.

Prompt engineering should be taught not just technically, but also strategically. The skill of talking to the machine effectively underpins any critical engagement with an LLM.

7.5.2 Recommendations for Future Research

The proposed combined framework is highly conceptual and derived qualitatively. Quantitative research would be appropriate to empirically test the model. Experimental designs could for instance compare learning outcomes with LLMs using this framework versus others.

Given the identified importance of learner intent, further research should explore the factors influencing the choice between deep learning and task completion. The effect could also be dependent on task type and further research could compare for example programming vs report writing.

This study focused on the trainers in an organisation. Future research should investigate the impact of this framework on learners in structured learning environments.

Longitudinal studies would also be appropriate to track the long-term impact of using this framework on skill development and metacognitive growth.

7.6 Limitations of the Study

Time Horizon

The rapid evolution of LLM technology itself presented a limitation. The capabilities and accessibility of AI tools are changing quickly and findings based on the state of technology during the study period (2025) might become outdated as new tools emerge.

Sample Selection

The study also acknowledges the potential for participant bias. The sample consisted of senior leaders who were acknowledged as early adopters or 'AI champions' within their organisations. Their perspectives influenced their responses and may not fully represent the views or challenges faced by the broader workforce less familiar with these tools. Although triangulation was employed throughout the development of Chapter 5 and Chapter 6 this potential bias likely remains.

Researcher Bias

The researcher's role in qualitative data collection and analysis introduced the possibility of researcher bias. As the primary instrument for data gathering and interpretation, the researcher's own assumptions and interpretations inevitably shaped the findings (Golafshani, 2003; Roulston, 2010).

Methodology

The qualitative, exploratory design and non-probability sampling method (purposive and snowball) limited the generalizability of the findings. The study aimed to generate contextual insights and develop theoretical understanding rather than produce statistically representative results (Saunders & Lewis, 2018).

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Addendum A: Consent Form

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA.

I am conducting research on how Large Language Models (LLMs) influence knowledge transfer in adult learning contexts, with a focus on Bloom's Taxonomy and Knowles's andragogical principles. Our interview is expected to last about an hour and will help us understand how these frameworks may need to adapt in AI-augmented learning environments.

All data will be reported without identifiers, ensuring your confidentiality is maintained. Interview recordings and transcripts will be securely stored for a minimum of 10 years on an encrypted, access-controlled platform, after which they will be permanently deleted.

Your participation is voluntary, and you can withdraw at any time without penalty. All data will be reported without identifiers. If you have any concerns, please contact my supervisor or me. Our details are provided below.

Researchers name:	Johannes Krapohl	Supervisors Name:	Dr Jeff Y-J Chen
Email	24072533@mygibs.co.za	Email:	chenj@gibs.co.za
Phone No.	0837087724	Phone no:	072 222 7119

Signature of the Participant:

Signature of the Researcher:

Date:

Date:

Addendum B: Pre-Interview Briefing

Understanding Knowles's Andragogy and Bloom's Taxonomy

As a participant in this research study, you will be reflecting on how artificial intelligence tools like ChatGPT are reshaping the way professionals learn. To help guide our conversation, this short document explains two widely used learning frameworks: Knowles's Andragogical Principles and Bloom's Taxonomy.

These models have long influenced how adult education and training are designed. However, with tools like LLMs (Large Language Models) becoming common in business settings, it's worth asking: Do these models still hold up?

This guide gives you a simple overview to ensure we have a shared understanding in our interview.

1. Knowles's Andragogy: Learning for Adults

Who was Malcolm Knowles?

Malcolm Knowles was a pioneer in the field of adult education. He introduced the concept of andragogy, which means the method and practice of teaching adult learners.

Unlike children, adults bring life experience into learning, prefer practical applications, and want to know why they are learning something. Knowles identified six key principles that define how adults learn best.

The Six Principles of Andragogy:

Principle	What It Means	Business Example
1. Need to Know	Adults need to understand *why* they need to learn something before committing time and effort.	A manager is more engaged in Excel training when it's linked to improving monthly report accuracy.
2. Self-Concept	Adults see themselves as self-directed learners. They want control over their learning journey.	Offering optional online modules allows employees to choose the pace and order of learning.
3. Prior Experience	Adults bring experience that can enrich learning, but also mental models that can block it.	During sales training, participants share past techniques and reflect on what worked or didn't.
4. Readiness to Learn	Adults are ready to learn things that are immediately relevant to their jobs or roles.	New team leaders eagerly take on performance coaching workshops before staff reviews.

5. Orientation to Learning	Adults prefer real-world, task-oriented learning—not abstract theory.	A negotiation course uses role-plays that mirror actual client scenarios.
6. Motivation to Learn	Internal motivators (job growth, satisfaction) often outweigh external ones (grades).	A marketing executive takes a digital analytics course to stay competitive, not just for a certificate.

2. Bloom's Taxonomy: Levels of Thinking

What is Bloom's Taxonomy?

Developed in 1956 by Benjamin Bloom and colleagues, Bloom's Taxonomy is a framework that classifies learning objectives based on the type of thinking required. It's often shown as a pyramid, where learners progress from basic recall to advanced creative thinking.

Below is a practical breakdown of the original taxonomy with clear, workplace-relevant language:

Step (Original Term)	Meaning	Quick Workplace Example
1. Knowledge	Remembering facts, terms, rules.	You can state a safety limit or a definition from memory.
2. Comprehension	Explaining what those facts mean.	You can describe why a safety limit matters for quality or risk.
3. Application	Using what you know in a real situation.	You follow the procedure correctly on shift or in a case study.
4. Analysis	Breaking things down; spotting causes and patterns.	You compare two runs and find where a deviation started.
5. Synthesis	Combining ideas to make something new.	You design a better checklist or process from what you learned.
6. Evaluation	Judging options against clear criteria.	You pick the best fix and justify it (safety, cost, time).

Traditionally, learners were expected to work their way up, mastering lower levels before tackling higher ones.

3. Why This Matters in the Age of AI

Tools like ChatGPT allow learners to jump straight to advanced outputs like summaries, emails, or business plans, sometimes skipping foundational stages like memorisation or basic understanding. While this saves time, it raises key questions:

- Are learners truly *learning* if AI does the remembering or applying for them?
- Can Bloom's and Knowles's models adapt to a world where AI is a learning partner?

That's what this study is about. Your insights will help us understand if these frameworks are still useful, or if they need to evolve.

Addendum C:
Interview Guide

Participant Background

1. Can you briefly describe your role in business education?
2. How familiar are you with using AI tools, such as ChatGPT, in your teaching or learning context?
3. What is your understanding of adult learning theories like Knowles's andragogy and/or Bloom's taxonomy?

Knowles's Andragogy (RQ1)

4. Main Question:
   In your experience, how has the use of LLMs affected the application of Knowles's andragogical principles in business education?

   4.1. Which of the six principles do you think is most affected?
   4.2. Do you believe LLMs can support adult learners' autonomy or self-directed learning and can you explain how?
   4.3. If not, what aspects of adult learning do you feel LLMs cannot support and why?
   4.4. Have you observed any concerns when LLMs are coupled with reflective or experiential learning?
   4.5. How can the framework be adapted for LLM use?

Bloom's Taxonomy (RQ2)

5. Main Question:
   In your opinion, how does the use of LLMs affect the cognitive levels of Bloom's Taxonomy in business education?

   5.1. Which of cognitive levels are most influenced by LLMs?
   5.2. Do you believe that LLMs can help learners jump directly to "Create" without building lower-level knowledge? Why do you think this is happening?
   5.3. If not, what aspects of the taxonomy do you believe remain unaffected and why?
   5.4. Do you feel the taxonomy can still apply in its traditional linear form when LLMs are introduced?
   5.5. How can the framework be adapted for LLM use?

Addendum D:
Interview code Table

Initial Code	Sub-theme	Main Theme
Learning driven by need	Making Learning Relevant	AI as an Enabler of Andragogy
Linking "Knowledge" to "Need to know"		
Motivation to Learn		
Value linked to career journey		
Positive reinforcement loop		
AI as an enabler of Andragogy		
Affective learning outcomes (satisfaction)		
AI enhances learner autonomy	Fostering Learner Autonomy	
Self directed learning		
AI personalization		
AI as an empowerment tool		
AI as a democratized expert		
Learner intent dictates AI's impact	Power of Learner Intent	
User mindset determines AI's creative impact		
Focus on practical skills over credentials		
Task completion vs. knowledge acquisition		
Contextual applicability of Andragogy		
Life stage/Generation as a contextual layer		
Proposed addition to Knowles (AI-augmented independence)		
Re-sequencing Bloom's Taxonomy	Iterative Learning Process	The Transformation of Bloom's Taxonomy
Iterative learning loop		
Add Feedback Loop to Bloom's		
Adapting Blooms (AI-Parallel version)		
Re-conceptualizing Bloom's (Hub-and-spoke model)		
Re-conceptualizing Bloom's (Soundboard model)		
AI as a parallel layer		
Primacy of foundational steps	Adequate Foundational Knowledge	
Cannot skip foundational steps		
Skipping foundational steps		
Contextual importance of memory		
Value of well presented theory		
AI as an analyses tool	Shifting to Higher-Order Thinking	
AI for Data visualization		
Distinction between evaluation and self-reflection		
Changing goal of learning		
Relevance of Bloom's linear structure		
Need to critically question AI output	Questioning the LLM	The Emergence of New Core Competencies
Using AI to teach critical evaluation		
Need for active comprehension		
Proactive source curation		

Skill of effective prompting	Talking to the Machine	
Selecting the appropriate AI tool		
Scoping AI for specific learning levels		
AI system requires closed-loop feedback		
Meta-cognition of learning frameworks required	Metacognition	
Pro-technology educator mindset		
Need for self reflection		
Process over content knowledge		
Paradigm shift: Process over content knowledge		
Proposed addition to frameworks (Value/Worldview)		
Theoretical Framework Integration		
Andragogy as the 'Why', Bloom's as the 'What'		
Bloom's nested within Andragogy		
Teaching transferable problem-solving skills	Building Transferable Skills	
Using AI for professional image		
AI for improving soft skills		
AI as a sparring partner / sounding board	AI as a Powerful Assistant	A Partner with Human-Centric Boundaries
AI as a competitive advantage		
Novel/Personal applications of AI		
AI as a barrier remover		
AI as a creative aid		
AI as a tool to overcome creative blocks (kill the critic)		
Efficiency in information gathering		
AI as information filter		
AI for virtual simulations/labs		
AI improves work efficiency		
AI as an instructional aid		
AI for translating technical concepts		
AI for anticipating learner needs		
AI enabling focus on human factors		
Data & tool fluency		
Hands-on training methodology		
Holistic training approach		
Sales/Marketing as education		
Peer-to-Peer learning		
Irreplaceability of human mentorship	Human Experience and Empathy	
Primacy of hands-on experience		
Inability to replicate non-verbal cues		
Experience as a filter for AI output		
Critical thinking as a human domain		
Creativity as a human domain		
Changing role of the educator		
RIsk of overreliance	Understanding the Risks	
Risk of plausible but incorrect answers		
Risk of shallow understanding		
Risk of informational echo chambers		
Atrophy of skills		

Risk of losing human intuition		
Limits of AI in learning		
Risk of misinformation (Values/Beliefs)		
Dismissal of AI detection tools		
Illusion of competence		