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Beyond the arms race: An exploratory study on shadow AI usage and competency risks among DBA students in Sarawak

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Abstract

The advent of generative artificial intelligence (AI) is affecting postgraduate education, particularly professional doctorates, which demand that candidates juggle full-time employment with the rigors of academic study. Generative artificial intelligence can improve efficiency and facilitate analytical thinking but also presents challenges regarding academic integrity, supervision, and the quality of doctoral learning. This study is a qualitative exploratory study exploring the phenomenon of shadow AI, the informal and covert use of generative AI for academic work, among Doctor of Business Administration students in Sarawak, Malaysia. Semi-structured interviews were conducted with five working DBA students who actively used generative AI tools. Data were analyzed using the constant comparative method, and four themes emerged: pragmatic survival, the verification shield, competency risk, and systemic disconnect. The findings suggest that students' engagement with shadow AI was not mainly intended to facilitate cheating but rather served as a means of dealing with workload pressures, reconciling professional and student identities, and managing ambiguous institutional policies on AI and academic integrity. However, long-term hidden dependence can erode cognitive capacity, professional judgment, and doctoral-level expertise. Focusing on detection may push AI further underground. The study synthesizes Shadow AI and Conservation of Resources theories to advocate transparent, human-centered, and assessment-based policies that acknowledge generative AI as a fixture of doctoral education while protecting independent thought, ethical practice, academic rigor, and core doctoral competencies.

Keywords: Academic integrity, Conservation of resources theory, Doctoral competency development, Doctoral education, Generative artificial intelligence, Shadow AI, Working professionals.

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Contents

Contribution of this paper to the literature

This study contributes to the literature by integrating the theories of Shadow AI and Conservation of Resources in professional doctoral education. The main contribution of the study is the discovery that hidden use of AI is a reflection of survival under workload, not of intentional dishonesty. This study documents the risks associated with cognitive ability, professional judgment and doctoral competence.

1. Introduction

Generative artificial intelligence (AI) systems, including large language models like ChatGPT, are now widely embedded in higher education. Postgraduate students frequently use these tools to brainstorm, summarise academic literature, structure arguments, and refine their academic writing (Dwivedi et al., 2023; Robert & McCormack, 2025; Strzelecki, 2024). In Doctor of Business Administration (DBA) programmes, this pattern is particularly visible. DBA candidates are typically experienced professionals in senior positions who must juggle demanding work responsibilities alongside the rigours of doctoral-level study (Al-Kumaim, Hassan, Mohammed, & Saleh, 2025).

Despite the clear advantages that generative AI can offer, its use has sparked serious concerns among scholars and regulators about academic integrity, deep learning, and the credibility of advanced skills certification. Critics argue that excessive reliance on AI may undermine independent thinking, blur the boundaries of authorship, and encourage surface-level engagement with complex issues (Cotton, Cotton, & Shipway, 2024; Selwyn, 2024). These concerns are especially acute at the doctoral level, where the award of a degree is meant to signal sophisticated analytical ability, rigorous methodological practice, and sound professional judgement.

In response, international and national bodies have begun to outline principles for responsible AI use. UNESCO (2023), for example, advances a human-centred approach that stresses transparency, accountability, and the importance of human agency. In Malaysia, the Malaysian Qualifications Agency (MQA) has recognised the legitimacy of generative AI use in higher education, if institutions establish responsible-use guidelines, require disclosure, and maintain human oversight (Malaysian Qualifications Agency, 2023). Nonetheless, emerging evidence suggests that students and staff often experience AI policies as ambiguous, unevenly applied, or difficult to interpret in practice (Chan, 2023; Smit, Wagner, & Bond-Barnard, 2025).

Within this context, students may gravitate towards shadow AI behaviours, understood as intensive yet largely hidden use of generative AI that occupies a grey zone of informal or weak regulation. In DBA programmes, which are designed to develop reflective professionals and strategic decision-makers, such shadow practices raise challenging questions about the effectiveness of management structures, the protection of academic integrity, and the reliability of competency verification. This study therefore investigates how DBA students in Sarawak experience, rationalise, and evaluate their shadow AI usage, and how they perceive its implications for both educational outcomes and occupational capabilities.

This research offers four key contributions to the growing shadow AI literature. First, it extends existing work by examining shadow AI within DBA education, a context that has received little attention to date. Second, it integrates Shadow AI Theory with Conservation of Resources Theory to explain how workload pressures and resource considerations shape AI adoption patterns among doctoral students. Third, it presents an empirically grounded framework consisting of four interconnected themes: Pragmatic Survival, Verification Shield, Competency Risk, and Systemic Disconnect, which sheds light on the institutional conditions, rationalisations, and risks underlying shadow AI use. Finally, it proposes practical and pedagogical recommendations for fostering human-centred AI governance in doctoral education, aiming to balance the benefits of innovation with the need to safeguard integrity and meaningful learning.

2. Literature Review

2.1. Generative AI in Higher Education

The integration of generative artificial intelligence (AI) into higher education has accelerated rapidly since the public release of large language models such as ChatGPT in late 2022. These systems, which can generate human-like text, summarise complex documents, create code, and support a variety of research tasks, have been widely taken up by both students and academics (Dwivedi et al., 2023; Strzelecki, 2024). For postgraduate students, generative AI offers attractive affordances: it can speed up literature reviews, enhance academic writing, help to structure arguments, and facilitate brainstorming (Robert & McCormack, 2025). In professional doctorate programmes such as the Doctor of Business Administration (DBA), where candidates are usually experienced professionals balancing demanding careers with advanced study, these efficiency gains are particularly compelling (Al-Kumaim et al., 2025).

However, the rapid spread of generative AI has also triggered significant scholarly concern. Critics caution that excessive reliance on AI tools may weaken independent critical thinking, blur authorship boundaries, and encourage shallow engagement with complex subject matter (Cotton et al., 2024; Selwyn, 2024). These concerns are especially acute at the doctoral level, where the qualification is expected to certify not only mastery of content but also the capacity for original, independent inquiry, rigorous methodology, and sound professional judgement.

2.2. Shadow IT and Shadow AI

The concept of shadow IT is well established in information systems research. It refers to the use of information technology systems, devices, software, or services outside the formal approval or oversight of an organisation's IT department (Kopper et al., 2018; Raković, Sakal, Matković, & Marić, 2020). Shadow IT typically arises when officially sanctioned systems are seen as overly restrictive, slow to respond, or poorly aligned with users' practical needs, prompting employees to adopt alternative solutions to meet work demands (van Acken, Jansen, Jansen, & Labunets, 2024). Under conditions of performance pressure and bureaucratic friction, such practices can become normalised and culturally embedded within workgroups.

Recent scholarship has extended this logic to artificial intelligence, introducing the term shadow AI to describe informal, unauthorised, or under-disclosed use of AI tools in organisational and educational settings (Audrerie, 2025; Kalisa, 2025; Silic, Silic, & Kind-Trüller, 2025). Shadow AI encompasses behaviours ranging from employees quietly using unapproved AI assistants to streamline workflows to students relying on generative AI for academic tasks without institutional awareness or supervision.

It is crucial to distinguish shadow AI from both legitimate AI use and academic misconduct. Legitimate AI use refers to transparent, disclosed, and institutionally sanctioned application of AI tools, guided by clear policies that define acceptable use cases, disclosure norms, and human oversight mechanisms (Malaysian Qualifications Agency, 2023; UNESCO, 2023). In such contexts, AI is positioned as a supported pedagogical or productivity aid. Academic misconduct, by contrast, involves intentional deception for unfair advantage, such as submitting AI-generated work as one's own without substantive original contribution, or using AI to bypass assessment requirements in ways that directly breach institutional rules (Cotton et al., 2024).

Shadow AI sits in a grey zone between these poles. It involves using AI tools in ways that are neither fully disclosed nor explicitly banned, often emerging when institutional policies are ambiguous, inconsistently enforced, or perceived as detached from practical realities (Chan, 2023; Smit et al., 2025). Users of shadow AI may not intend to deceive. Rather, they adopt these tools as a pragmatic response to pressures such as time scarcity, cognitive overload, or unclear guidance. Nonetheless, because this usage remains hidden or only partially disclosed, it evades institutional oversight and may gradually normalise practices that undermine learning outcomes and professional competence. This study adopts this nuanced conceptualisation of shadow AI as its central investigative lens.

2.3. Governance Ambiguity and Integrity Reframing

The governance of generative AI in higher education is evolving rapidly and remains fragmented. International organisations have begun to articulate high-level principles for responsible AI use. UNESCO (2023) promotes a human-centred approach that emphasises transparency, accountability, human agency, and the protection of fundamental rights. In Malaysia, the Malaysian Qualifications Agency (MQA) has acknowledged the legitimacy of generative AI in higher education, provided that institutions develop responsible-use guidelines, require disclosure of AI assistance, and maintain human oversight of AI-generated outputs (Malaysian Qualifications Agency, 2023).

Despite these initiatives, empirical evidence indicates that many institutional AI policies are experienced by students and staff as ambiguous, unevenly implemented, or poorly communicated (Chan, 2023; Smit et al., 2025). This governance ambiguity creates fertile ground for moral hazard. Smit et al. (2025) argue that unclear regulations can lead students to adopt ethically questionable practices while convincing themselves that they are not technically breaking any rules. Chan (2023) further stresses that effective AI governance requires not only policy clarity but also sustained AI literacy development and ongoing ethical dialogue among all stakeholders.

Debates about governance are complicated by tensions between detection-focused and pedagogically oriented strategies. Some institutions have invested heavily in AI-detection software, seeking to identify unauthorised AI use through automated means. Critics, however, contend that such approaches are technically unreliable, subject to circumvention, and may push AI use further underground, reinforcing a climate of suspicion rather than trust (Selwyn, 2024; Spiller, 2025). Emerging scholarship instead advocates anticipatory governance models that frame AI as a partner within human–AI complementarity, embedded in human monitoring and reflective practice rather than treated solely as a threat to be detected and punished (Autenrieth & Schluchter, 2025; Selvam & Vallejo, 2025).

2.4. Theoretical Gaps and Research Need

Existing literature offers important insights into generative AI adoption, shadow IT, and governance challenges around emerging technologies. Nonetheless, several critical gaps remain. First, while shadow AI has been explored in organisational and HR contexts (Audrerie, 2025; Kalisa, 2025), its specific manifestations in doctoral education—particularly in professional doctorates such as the DBA are still largely underexamined. Second, there is limited theoretical integration that explains why doctoral students, who are themselves experienced professionals, engage in shadow AI practices despite awareness of potential risks to competency. Third, there is little empirically grounded understanding of how students perceive and rationalise the tension between immediate survival needs and long-term professional development.

This study addresses these gaps by investigating shadow AI usage among DBA students in Sarawak, Malaysia. Drawing on Shadow AI Theory and Conservation of Resources (COR) Theory, it seeks to illuminate the motivational drivers, ethical rationalisations, competency risks, and institutional conditions that shape shadow AI practices in this under-explored population.

3. Theoretical Framework

This study is guided by two complementary theoretical lenses: shadow AI theory and Conservation of Resources (COR) theory. Shadow AI theory, rooted in the broader shadow IT literature, explains how unclear, restrictive, or poorly aligned governance environments can encourage covert technology use by framing compliance requirements as obstacles rather than supports (Kalisa, 2025; Kopper et al., 2018). In educational settings, such conditions may normalise hidden AI practices as a pragmatic way for students to "get things done" while avoiding scrutiny.

Conservation of Resources theory holds that individuals seek to obtain, retain, and protect valued resources such as time, mental energy, and cognitive effort, with these preservation tendencies becoming more pronounced under prolonged or intense stress (Hobfoll, 1989; Hobfoll, Halbesleben, Neveu, & Westman, 2018). Applied to AI use, COR theory suggests that DBA students turn to generative AI as a strategy to conserve depleted resources and maintain performance amid heavy workloads. At the same time, habitual reliance on these resource-saving strategies can generate longer-term losses in skills, confidence, and deep understanding, raising questions about competence and professional development.

4. Research Methodology

This research adopts a qualitative interpretivist approach to explore how DBA candidates perceive and experience shadow AI in their everyday academic lives (Creswell & Poth, 2018). An interpretivist stance recognises that AI use is shaped by personal contexts, meanings, and negotiations rather than being a fixed or purely measurable phenomenon. Using purposive sampling, five working professionals currently enrolled in doctoral programmes at Malaysian universities in Sarawak, and who regularly use generative AI tools, were invited to participate in the study.

Participants took part in semi-structured interviews lasting between 45 and 60 minutes, focusing on their reasons for using AI, their ethical views, their understanding of university policies, and their perceptions of how AI affects their learning and professional work (Creswell & Poth, 2018). All interviews were transcribed, after which a constant comparative analysis informed by grounded theory procedures was used to analyse the data. Trustworthiness was supported through reflective memo-writing, peer debriefing, and careful documentation of analytic decisions throughout the research process.

Ethical compliance was ensured by obtaining informed consent, protecting both participant and institutional anonymity, and handling any information that indicated potential policy concerns with particular care. The researcher actively sought to ease participants' worries, emphasised confidentiality, and clarified that the purpose of the study was to understand their experiences rather than to judge or criticise their use of AI.

5. Data Analysis

The constant comparative method was employed to analyse the qualitative interview data, using a three-stage coding framework comprising open coding, axial coding, and selective coding. This structured procedure enabled the progressive movement from raw participant accounts to higher-order conceptual themes, while maintaining close grounding in the empirical material (Glaser & Strauss, 1967).

Five semi-structured interviews with DBA candidates were transcribed verbatim and analysed iteratively. During analysis, comparisons were made within and across cases to identify recurring patterns, similarities, and conceptual contrasts related to shadow AI use, ethical rationalisations, and perceived risks to competency. This iterative comparison helped sharpen the emerging categories and ensured that the final themes reflected the lived complexities of participants' shadow AI practices.

5.1. Participant Profile

Table 1 outlines the background information of the participants. The sample reflects diversity across professional sectors, including engineering, government, finance, and education. Despite this diversity, all participants reported high workload intensity, ranging from 8 to 10 on a 10-point scale, emphasising sustained role conflict between professional responsibilities and doctoral study.

Table 1. Demographic profile of participants.

Participant ID	Gender	Current Profession / Role	Industry / Sector	Self-Reported Workload Intensity
P1	Male	Senior Consultant Engineer	Consultancy Firm	8–9 / 10
P2	Female	Training Consultant	Federal Government	8–9 / 10
P3	Male	Finance Officer	State Government	10 / 10
P4	Male	Senior Lecturer	Higher Education	8 / 10
P5	Female	Academic Staff	TVET Education	8 / 10

The consistently high workload levels provide important contextual grounding for interpreting AI use as a coping and resource-conservation strategy rather than isolated individual choice.

5.2. Coding Process and Theme Development

Phase 1: Open Coding

The first stage of analysis involved a detailed, line-by-line review of the interview transcripts. A total of 33 raw verbatim excerpts were initially extracted and assigned open codes that captured distinct units of meaning. Through iterative comparison, overlapping codes were merged, resulting in 29 consolidated open codes. Conceptual saturation was reached, as the key ideas appeared consistently across different participants. The full open-coding matrix is presented in Appendix 1.

Phase 2: Axial Coding

In the axial coding phase, the 29 open codes were grouped into higher-order categories that explained why shadow AI is used and what consequences it generates. On the driver side, five axial categories emerged: Operational Efficiency and Speed, Cognitive Offloading, The Kickstarter (overcoming writer's block), Drafting and Polishing, and Ethical Rationalisation. On the consequence side, four axial categories were identified: Mental Sharpness Decline, Professional Erosion, Output Quality Issues, and Shadow Culture. These categories are summarised in Table 2.

Table 2. Summary of axial coding categories.

Drivers of Shadow AI Use	Risks and Tensions
Operational Efficiency & Speed	Mental Sharpness Decline
Cognitive Offloading	Professional Erosion
The "Kickstarter" (overcoming writer's block)	Output Quality Issues
Drafting & Polishing	Shadow Culture
Ethical Rationalisation	

Phase 3: Selective Coding

During the concluding phase, the axial categories were synthesised into four overarching themes that reflect the central features of shadow AI practices among DBA students.

Table 3. Selective coding matrix (Themes and categories).

Theme	Constituent Categories
Pragmatic Survival	Operational Efficiency, Cognitive Offloading, The Kickstarter, Drafting & Polishing
Verification Shield	Ethical Rationalisation, Dependency
Competency Risk	Mental Sharpness Decline, Professional Erosion, Output Quality Issues
Systemic Disconnect	Shadow Culture, Compliance Illusion

6. Results

This section presents the four themes identified through selective coding. Each theme is described using participant voices to illustrate its meaning and scope. Interpretative commentary is reserved for the Discussion section that follows.

6.1. Theme 1: Pragmatic Survival

Participants consistently framed AI as a practical necessity for managing competing demands. AI functioned as a productivity amplifier, anxiety reducer, and entry point into cognitively demanding tasks.

Operationally, they described AI as essential for handling "firefighting mode" at work and switching quickly into student mode:

- "During office hours, I am more in firefighting mode, handling operations and responding to immediate needs." P2
- "It is tough for me to spare time... I use AI to shorten reading time." P3
- "I need to move faster to handle overlapping tasks." P2

AI was likewise engaged as a tool that helped ease end-of-day stress and provided a mental boost when fatigue set in:

- "At the end of a long day... AI helps me break the block by proposing a structure, so I do not have to start from zero." P1
- "It is useful when I need to start a blank report. I ask it for headers and subheaders." P1
- "It helps me overcome 'do not know how to start'." P5
- "After a full day, I can feel mentally drained. It helps reduce the stress." P5

These verbatim accounts show AI acting simultaneously as a time saver and an emotional support, enabling basic academic functioning under severe role conflict.

6.2. Theme 2: The Verification Shield

Ethical comfort was achieved not through disclosure but through verification and detection avoidance. Integrity was operationalised as "checking" outputs and staying within similarity thresholds.

Participants explicitly framed their ethics around verification:

- "The problem is when students accept without checking. That is dangerous." P1
- "I see AI as a behind the scenes assistant. I keep a human-in-the-loop approach." P1

They also tied "guilt" to plagiarism detection limits:

- "In terms of guilty conscience I would not... as long as you work within the means Turnitin." P3
- "It helps me create a guilt-free usage because I am only using it for ideas, not copy pasting." P3

These verbatim statements illustrate the "Verification Shield," where checking, editing and passing Turnitin are treated as sufficient markers of integrity, even when AI use remains undisclosed.

6.3. Theme 3: The Competency Risk

Despite heavy use, participants expressed concern about erosion of deep thinking, professional intuition, and independent analytical capacity, often using embodied metaphors such as "brain muscle" and "hollow expert."

On mental sharpness and deep thinking, participants reported:

- "If you use it for everything, you will underuse ability to critique." Shallow P4
- "You have not trained your brain muscles. It is like going to the gym and watching someone else lift weights." P4
- "Students might rely too much on it and forget how to do a literature review manually." P4
- "One risk is that I might lose habit of thinking deeply or writing from scratch." P5
- "It encourages surface level mastery because I only read the summary." P3

The repeated "brain muscle" metaphor used by participants also parallels evidence that disuse of skeletal muscle is associated with declines in cognitive function, reinforcing the idea that underused cognitive capacities may weaken over time (Sui, Williams, Holloway-Kew, Hyde, & Pasco, 2021). From a Conservation of Resources perspective, this suggests that while AI helps conserve time and energy in the short term, it may also contribute to gradual losses in cognitive resources if deep reading and critical writing are repeatedly outsourced (Hobfoll, 1989; Hobfoll et al., 2018). On professional erosion and the "hollow expert" worry, they stated:

- "The biggest risk is erosion of... engineering intuition if someone starts to accept AI outputs without checking." P1
- "There is a danger engineers will know the answer but not the reasoning behind it." P1
- "If we always ask AI to summarise, we might lose the tacit knowledge of how policies connect." P2

Participants also pointed to quality flaws in AI output:

- "Sometimes it introduces subtle errors in calculations or facts that look real but are wrong." P1
- "Sometimes the output is too clean, resulting in a loss of public service flavour or local context." P2

These verbatim excerpts collectively support the theme that shadow AI, while helpful, is perceived as carrying significant long-term competency risks.

6.4. Theme 4: Systemic Disconnect

A clear gap emerged between institutional rhetoric on responsible AI use and the lived realities of DBA students. This disconnected normalised shadow practices and discouraged open supervisory dialogue.

Participants described AI as part of an informal, undocumented layer of support.

- "We use it, but the support is not recorded anywhere. It is an informal tool." P2
- "There is a fear of judgment if supervisors think we did not write it ourselves." P2

Because AI use was simultaneously widespread and officially "off the record," students navigated their practice through peer norms and personal rationalisation rather than clear programme guidance. This systemic disconnect reinforced the shadow culture that frames all three earlier themes.

7. Discussion

This section interprets the findings in light of the theoretical framework and existing literature, linking the four emergent themes to broader scholarly debates and practical implications.

7.1. Pragmatic Survival

The first and most prominent theme, Pragmatic Survival, captures how participants framed generative AI as an essential coping tool in the face of sustained workload pressure, role conflict, and cognitive fatigue. Across all five participants, AI use was described as pragmatic rather than aspirational. They did not present AI as a substitute for learning, but to remain functional amidst competing professional, personal, and academic demands.

Participants reported using AI to speed up routine academic tasks, such as summarising lengthy documents, proposing report structures, generating outlines, and refining language after long workdays. These practices mirror the axial categories of Operational Efficiency and Speed, Cognitive Offloading, The Kickstarter, and Drafting and Polishing. Expressions like "breaking the blank page," "moving faster," and "cutting short reading time" reflect an environment characterised by chronic time scarcity rather than opportunistic misconduct.

Theoretically, this theme aligns closely with Conservation of Resources (COR) theory, which posits that individuals under prolonged pressure adopt strategies to preserve diminishing resources such as time and cognitive energy (Hobfoll, 1989; Hobfoll et al., 2018). For DBA candidates, generative AI operates as a resource-preservation mechanism that enables continued engagement in doctoral study under conditions that might otherwise encourage disengagement or attrition. This finding resonates with recent work showing AI adoption as a coping response among working professionals in higher education (Al-Kumaim et al., 2025) as well as broader evidence that students use generative AI to manage workload and time pressure (Dwivedi et al., 2023; Strzelecki, 2024).

At the same time, while this survival-oriented framing is understandable and often justified, it creates conditions in which AI use becomes normalised without systematic reflection on its longer-term implications for deep learning and competency development.

7.2. The Verification Shield

The second theme, The Verification Shield, shows how participants constructed ethical comfort around AI use through verification and compliance-oriented rationalisations. Instead of conceptualising integrity in terms of transparency or genuine ownership of the intellectual process, participants frequently equated ethical use with checking AI outputs, editing the final text, and staying within the acceptable limits of plagiarism detection software.

Statements such as "as long as it passes Turnitin" and "I am only using it for ideas" illustrate a shift from normative academic integrity toward what can be described as a compliance illusion. In this mindset, integrity is framed as meeting technical thresholds rather than engaging in reflective or dialogic practices. Dependence on AI was often acknowledged but then neutralised through assurances of "human-in-the-loop" oversight.

This theme reflects broader insights from shadow IT and shadow AI literature, where users justify unofficial technology use by redefining compliance boundaries to align with performance demands (Kalisa, 2025; Kopper et al., 2018). In educational contexts, these rationalisations are reinforced when institutional AI policies are experienced as vague, inconsistently applied, or disconnected from everyday realities. Detection-focused or prohibitionist responses may intensify this trend, encouraging students to treat integrity primarily as avoiding sanctions or detection rather than as a commitment to transparent authorship and deep learning (Chan, 2023; Cotton et al., 2024; Smit et al., 2025; Spiller, 2025).

Importantly, the verification shield does not suggest complete moral disengagement. Rather, it indicates ethical adaptation under ambiguous governance conditions. Nonetheless, this adaptation risks narrowing integrity discourse to detection avoidance, echoing the moral hazard concerns raised by Chan (2023) and Smit et al. (2025) in relation to unclear AI regulations.

7.3. Competency Risk

Despite strong pragmatic justifications for AI use, participants expressed notable anxiety about its potential impact on learning quality and professional capability. The theme of Competency Risk brings together the axial categories of Mental Sharpness Decline, Professional Erosion, and Output Quality Issues, highlighting fears about long-term skill degradation.

Participants voiced concerns about losing the habit of deep reading, struggling to sustain critical thinking, and weakening their professional judgement. They described this as "not training the brain muscle" and "knowing the answer but not the reasoning," capturing the perceived risk of becoming practitioners who can produce acceptable outputs without truly grasping the underlying knowledge.

These worries align with emerging discussions of the "cognitive atrophy paradox" in AI–human interaction, where AI-driven efficiency may enhance short-term performance but compromise long-term cognitive resilience if deep thinking is repeatedly outsourced (Kabashkin, 2025; Roxin, 2025; Selwyn, 2024). From a COR perspective, when students consistently use AI to conserve time and mental energy, they may unintentionally set in motion a gradual decline in cognitive resources by repeatedly bypassing deep reading, critical analysis, and independent writing (Hobfoll, 1989; Hobfoll et al., 2018).

Crucially, the data do not suggest that participants were indifferent to these risks. Rather, they described a persistent tension between immediate survival needs and long-term competency preservation. This observation reinforces that shadow AI use among DBA candidates is not naïve or careless, but deeply ambivalent and self-aware.

7.4. Systemic Disconnect

The final theme, Systemic Disconnect, captures the structural conditions that sustain shadow AI practices. Participants consistently described a gap between high-level institutional policy statements and the realities of everyday academic practice. AI use was seldom discussed explicitly in supervision meetings, and formal mechanisms for disclosure were either absent or poorly integrated into programme workflows.

This silence contributed to a shadow culture in which AI use was widespread yet rarely acknowledged. Fear of judgement and uncertainty about supervisors' expectations discouraged open dialogue, encouraging concealment rather than transparency. In this context, integrity became individualised and defensive, rather than collectively negotiated and guided by educational aims.

This theme directly echoes shadow AI theory, which suggests that when governance frameworks fail to align with user realities, technology use drifts into informal, unregulated spaces (Silic et al., 2025). Detection-focused strategies, rather than resolving this disconnect, may push AI use further underground by shifting attention from learning and development to risk management (Selwyn, 2024). Similar patterns have been observed among knowledge workers who quietly embed AI into their workflows while outwardly conforming to non-AI norms a dynamic (Mollick, 2023) describes as becoming a "secret cyborg."

The systemic disconnect observed in this study parallels findings from research on both shadow IT and shadow AI. When there are persistent gaps between official policies and actual technology practices, informal and unregulated use often flourishes (Kalisa, 2025; Kopper et al., 2018; Raković et al., 2020; Silic et al., 2025; van Acken et al., 2024). Commentators and industry reports argue that if organisations focus primarily on detection, without investing in AI literacy or encouraging open conversation, AI use is likely to become even more hidden. This trajectory makes it harder to build trust and shared norms around responsible AI use (Robert & McCormack, 2025; Spiller, 2025; UNESCO, 2023).

8. Propositions

Based on empirical findings and supported by theoretical lenses, the study advances the following propositions:

Proposition 1: Under conditions of sustained workload intensity and role conflict, DBA students are likely to adopt generative AI as a coping and resource-protection strategy rather than as deliberate academic misconduct (Al-Kumaim et al., 2025; Hobfoll, 1989; Hobfoll et al., 2018).

Proposition 2: Ambiguous or detection-focused AI governance encourages verification-centred ethical rationalisations, where integrity is defined by technical compliance rather than transparency (Chan, 2023; Smit et al., 2025).

Proposition 3: Persistent reliance on shadow AI for cognitively demanding tasks increases the risk of competency erosion, including reduced deep thinking, weakened professional intuition, and hollow expertise (Kabashkin, 2025; Roxin, 2025).

Proposition 4: A systemic disconnect between institutional AI policies and supervisory practice reinforces shadow AI cultures and discourages open dialogue about AI use in doctoral education, echoing similar shadow dynamics reported among knowledge workers and HR professionals (Audrerie, 2025; Kalisa, 2025; Silic et al., 2025).

9. Conclusion

This study demonstrates that shadow AI use among DBA students is best understood as a structurally induced response to sustained workload pressure rather than deliberate academic misconduct. While generative AI supports academic survival, its informal and undisclosed use poses risks to cognitive sovereignty, professional judgment, and the development of doctoral-level competencies. The findings enrich the literature by extending the notion of shadow AI into doctoral education and showing how covert AI practices emerge as adaptive strategies in the face of heavy workloads and role conflict. The study proposes an innovative explanatory framework that integrates Shadow AI Theory with Conservation of Resources Theory and comprises four themes: Pragmatic Survival, Verification Shield, Competency Risk, and Systemic Disconnect. It also offers an exploratory qualitative approach for investigating hidden AI practices and underscores the need for transparent, human-centered AI governance that safeguards the development of doctoral-level competencies.

Moreover, governance strategies focused mainly on detection are insufficient and may inadvertently reinforce shadow practices. DBA programmes should instead adopt human-centred, dialogic AI governance that emphasises transparency, supervisory engagement, AI literacy, and assessment designs that make students' reasoning processes visible. By recognising AI as an enduring feature of doctoral education, institutions can move beyond an arms-race mentality and better protect the core purposes of doctoral study.

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Appendixes.

Appendix 1. Full open coding matrix (33 Data Points).

No.	Participant	Raw Data (Verbatim Excerpt)	Context / Scenario	Initial Open Code
1	P1	"Sometimes I need to draft technical notes quickly, so I put the raw points in and ask it to structure them."	Using AI as a scribe to speed up routine writing tasks.	Drafting Assistant
2	P1	"At the end of a long day... AI helps me break the block by proposing a structure, so I don't have to start from zero."	Mental exhaustion causing inertia; AI acts as a starter.	Break Mental Block
3	P1	"It is useful when I need to start a blank report. I ask it for headers and sub-headers."	Overcoming the intimidation of an empty document.	Bypass Blank Page
4	P1	"It is good at proposing a structure for my arguments, which I then fill in with my own data."	AI used for logical organization, not content generation.	Ideation
5	P1	"The biggest risk is erosion of... engineering intuition if someone starts to accept AI outputs without checking."	Fear that relying on AI dulls professional instincts.	Erosion of Intuition
6	P1	"There is a danger engineers will know the answer but not the reasoning behind it."	The outcome is correct, but the human lacks the knowledge.	Hollow Expert
7	P1	"Sometimes it introduces subtle errors in calculations or facts that look real but are wrong."	The risk of AI "hallucinations" appearing credible.	Accuracy Errors
8	P1	"The problem is when students accept without checking. That is dangerous."	Blind trust in the tool leading to professional negligence.	Dependency

No.	Participant	Raw Data (Verbatim Excerpt)	Context / Scenario	Initial Open Code
9	P1	"I see AI as a behind-the-scenes assistant. I keep a human-in-the-loop approach."	Justifying usage by claiming oversight responsibility.	Ethical Rationalization
10	P2	"During office hours, I'm more in firefighting mode, handling operations and responding to immediate needs."	High-pressure work environment leaves no time for study.	Firefighting Mode
11	P2	"I often use it to summarise a long circular or policy document so I don't have to read the whole thing."	Reducing cognitive load by skipping full reading.	Summarize Long Articles
12	P2	"By the time I get to study, I need to move faster because I have very little time left."	Usage driven purely by lack of time (Temporal Scarcity).	Operational Speed
13	P2	"Sometimes the output is too clean, resulting in a loss of public service flavour or local context."	The output feels robotic or detached from reality.	Generic Output
14	P2	"We use it, but the support is not recorded anywhere. It's an informal tool."	The tool is used secretly without official policy support.	Shadow / Hidden Use
15	P2	"There is a fear of judgment if supervisors think we didn't write it ourselves."	Psychological fear driving the secrecy.	Shadow / Hidden Use
16	P2	"If we always ask AI to summarise, we might lose the tacit knowledge of how policies connect."	Long-term loss of deep professional understanding.	Professional Erosion
17	P3	"I use AI to cut short time reading journals. I just need the methodology."	Efficiency strategy to bypass lengthy literature reviews.	Save Time / Cut Short
18	P3	"It is tough to spare time... my schedule is packed 10 out of 10."	Extreme role conflict between job and study.	Shift Gears (Fast/Slow)
19	P3	"I upload the PDF and ask it just to highlight the main findings."	Extracting specific data points without reading.	Highlight Key Points
20	P3	"I don't need the details, I just need to get the gist of the argument."	Prioritizing breadth over depth of understanding.	Get the Gist
21	P3	"It encourages surface-level mastery because I only read the summary."	Awareness that learning is becoming shallow.	Surface-Level Mastery
22	P3	"In terms of guilty conscience, I would not... as long as you work within the means [Turnitin]."	Defining ethics by whether the plagiarism checker catches it.	Compliance Illusion
23	P3	"It helps me create a guilt-free usage because I am only using it for ideas, not copy-pasting."	Internal negotiation to alleviate guilt.	Compliance Illusion
24	P4	"If you use it for everything, you will underuse ability to critique."	Atrophy of critical thinking skills due to disuse.	Shallow Understanding
25	P4	"You have not trained brain muscle. It is like going to the gym and watching someone else lift weights."	Metaphor for cognitive decline (Mental Sharpness).	Brain Muscle Weakness
26	P4	"Students might rely too much on it and forget how to do a literature review manually."	Permanent loss of academic skills (De-skilling).	De-skilling
27	P4	"It creates a dependency risk where you cannot write without opening the tool first."	Psychological addiction to the tool's assistance.	Dependency
28	P5	"It helps me overcome 'don't know how to start'."	Breaking the initial paralysis of writing.	Facilitating
29	P5	"I write my points roughly, then ask it to tidy up... customize the tone to be more academic."	Using AI as a polisher/editor rather than a creator.	Improve Language/Tone
30	P5	"I use it to suggest an outline based on my variables."	Structural assistance for academic papers.	Generate Outlines
31	P5	"It helps me edit and customize the messy sentences I wrote."	Refining syntax and grammar for professional presentation.	Tidy up Wording
32	P5	"After a full day, I can feel mentally drained. It helps reduce the stress."	Emotional regulation; using AI to manage burnout.	Reduce Anxiety
33	P5	"One risk is that I might lose habit of thinking deeply or writing from scratch."	Fear of losing the ability to engage in deep cognition.	Lack of Deep Thinking

This phase highlights the richness of participants' experiences, ranging from pragmatic uses of AI for drafting, summarizing, and emotional regulation, to concerns about professional erosion, dependency, and ethical ambiguity.

Appendix 2 shows the process of data reduction and code consolidation following the open coding stage. It depicts the iterative comparison of 33 initial excerpts to find conceptual similarities and overlaps between participants. The linguistically different fragments that mirror the same underlying phenomenon are merged, resulting in 29 unique open codes. This consolidation suggests the reemergence of salient concepts across participants and indicates that the point of conceptual saturation has been reached.

Appendix 2. Data reduction and code consolidation – refined open code.

Following open coding, the 33 initial excerpts were subjected to iterative comparison to identify conceptual overlap. Although the excerpts differed linguistically and originated from different participants, several represented the same underlying phenomenon. These were therefore consolidated.

This reduction process resulted in 29 unique open codes, indicating that conceptual saturation had been reached, as key ideas were independently reported across participants.

Code Consolidation Logic

Table 4 illustrates the analytical logic used to merge semantically equivalent excerpts into single conceptual codes. The table demonstrates transparency in the reduction process and strengthens the audit trail.

Table 4. Data Reduction and Code Consolidation Matrix

Finalised Open Code	Primary Data Source	Secondary Data Source	Analytical Justification
Dependency	P1.8	P4.4	Both describe loss of autonomous functioning due to reliance on AI
Compliance Illusion	P3.6	P3.7	Both reflect ethics defined by plagiarism detection thresholds
Shadow / Hidden Use	P2.5	P2.6	Fear of judgement explains non-disclosure behaviour
Erosion of Intuition	P1.5	P2.7	Loss of tacit professional judgement across disciplines

This consolidation confirms that shadow AI is not idiosyncratic but structurally patterned across

Refined Open Codes – 29 Data Points

After consolidation, the final dataset consisted of 29 open codes, divided into 17 motivation-related codes and 12 risk-related codes.

Category	No.	Open Code Label	Participant Evidence (Key Phrase)
MOTIVATIONS (17 Codes)	1	Facilitating	P5: "overcome don't know how to start"
	2	Save Time / Cut Short	P3: "cut short time reading"
	3	Drafting Assistant	P1: "draft technical notes"
	4	Break Mental Block	P1: "break the block"
	5	Summarize Long Articles	P2: "summarise a long article"
	6	Improve Language/Tone	P5: "tidy up... customize"
	7	Firefighting Mode	P2: "firefighting mode"
	8	Ideation	P1: "proposing a structure"
	9	Shift Gears (Fast/Slow)	P3: "tough to spare time"
	10	Highlight Key Points	P3: "just to highlight"
	11	Generate Outlines	P5: "suggest an outline"
	12	Tidy up Wording	P5: "edit and customize"
	13	Get the Gist	P3: "get the gist"
	14	Reduce Anxiety	P5: "mentally drained"
	15	Bypass Blank Page	P1: "start a blank report"
	16	Multitasking Aid	P5: "overlapping tasks"
	17	Operational Speed	P2: "move faster"
RISKS (12 Codes)	18	Shallow Understanding	P4: "underuse ability"
	19	Erosion of Intuition	P1: "erosion of... engineering intuition"
	20	Surface-Level Mastery	P3: "just to highlight" (Skipping depth)
	21	Brain Muscle Weakness	P4: "not train brain muscle"
	22	Hollow Expert	P1: "know the answer but not the reasoning"
	23	Accuracy Errors	P1: "subtle errors"
	24	Generic Output	P2: "loss of public service flavour"
	25	Dependency	P1: "accept without checking"
	26	Shadow / Hidden Use	P2: "support is not recorded"
	27	Compliance Illusion	P3: "within the means" (Turnitin)
	28	Lack of Deep Thinking	P5: "lose habit of thinking deeply"
	29	De-skilling	P4: "rely too much"

This distinction reveals an important analytical tension: The same tool that enables survival and productivity also generates anxieties about cognitive decline, professional erosion, and integrity in ethics.