# AI-adoption attitudes in Southern Africa's higher education sector: A pilot survey using the capability, opportunity, motivation and behaviour (COM-B) model

**Mark E. Patterson**
*Associate Professor, School of Pharmacy, University of Missouri-Kansas City*
*https://orcid.org/0000-0002-2600-6887*

**Johan Breytenbach**
*Senior Lecturer, Department of Information Systems, University of the Western Cape, Cape Town*
https://orcid.org/0000-0001-7883-7140

**Ian Coffman**
*Pharm.D. Candidate, School of Pharmacy, University of Missouri-Kansas City*
https://orcid.org/0009-0000-6581-9285

**Abstract**
Artificial intelligence (AI) drives innovation but faces numerous potential challenges to adoption. This pilot survey applied the capability, opportunity, motivation and behaviour (COM-B) model to examine AI adoption attitudes in the Southern African higher education sector. The study sought to evaluate the extent to which the COM-B framework, rooted in behavioural science, can generate AI-adoption insights that would be complementary to insights generated by established information systems (IS) adoption models, such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT). Potential facilitators and barriers with respect to adoption of AI tools adoption were mapped against COM-B domains to develop a 10-point Likert-type scale survey that was piloted with 33 individuals working in the Southern African higher education sector. The findings identified key facilitators of AI as adequate technological infrastructure, readiness to address clients' ethical concerns, and beliefs that AI tools benefit clients. The dominant barrier identified was clients' potential ethical concerns regarding AI use in decision-making.

**Keywords**
artificial intelligence (AI), adoption; higher education sector, Southern Africa, capability, opportunity, motivation and behaviour (COM-B) model

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## 1. Introduction

Artificial intelligence (AI) is acknowledged as being a catalyst for socioeconomic development, propelling technological innovation across various sectors and fostering economic growth (Brynjolfsson & McAfee, 2014). In areas such as healthcare, education, and finance, AI applications offer the promise of greater efficiency and enhanced decision-making. However, these positive outcomes are often counterbalanced by challenges, including limited expertise, scarce resources, and unresolved ethical dilemmas (Binns, 2018). Understanding the core factors that drive AI adoption is critical for formulating effective implementation strategies.

Recent studies have highlighted the increasing importance of end-user attitudes and perceptions in shaping AI adoption outcomes, even within environments that possess strong IT infrastructure (Cocosila & Archer, 2017; Dwivedi et al., 2019). For instance, it has been found that sceptical end-user attitudes towards the accuracy or ethical implications of AI in healthcare often outweigh users' technical capabilities and create adoption barriers (Binns, 2018). Other factors found to be linked to AI-adoption resistance include fears of job displacement and concerns over AI's mimicking of human roles in education (Akinwalere & Ivanov, 2022). Recent advances in generative, agentic, and robotic AI are enabling increasingly adaptive human–machine interactions, thus adding complexity to the cognitive and behavioural factors influencing technology adoption (Obrenovic et al., 2024).

In behavioural science, the capability, opportunity, motivation and behaviour (COM-B) model is used to understand factors leading to behaviour change (Cane et al., 2012; Michie et al., 2011). While frequently applied in healthcare settings, including nursing and psychology (de la Fuente Tambo et al., 2024; Luo et al., 2024), COM-B has generally not been used in the context of behaviour change linked to adoption of technology. Technology adoption is typically explored through information systems (IS) models, and, in particular, through the technology acceptance model (TAM), and the unified theory of acceptance and use of technology (UTAUT).

The core aim of this pilot study was to explore the extent to which applying the COM-B model to the analysis of AI-adoption attitudes could generate findings that would complement findings from IS-focused frameworks, such as TAM and UTAUT. Our view is that expansion of the analytic lens for AI adoption to include capability, opportunity, motivation and behaviour domains has the potential to allow IS frameworks to offer more nuanced insights. The emphasis of COM-B on individual capability, environmental opportunities, and motivational factors would appear to make it well-suited for exploring socio-technical attitudes (Michie & West, 2013), and thus applicable to identifying individual end-user attitudes towards AI adoption. Also, although COM-B has been successfully used in South Africa to describe adoption of non-technological elements (see Marsh et al., 2021), the model's applicability to the country's technology-focused settings remains unexplored.

In South Africa, wide and systemic socio-economic inequalities create an environment characterised by a strong tension between AI's innovative potential and wide disparities in end-user capacity to harness this potential. While South Africa is emerging as a regional leader in AI innovation, particularly through startups focused on social impact (Dada & Van Belle, 2023; Opesemowo & Adewuyi, 2024), persistent disparities in education, income, and digital literacy have the potential to hinder broad adoption (Ganapathy et al., 2024). While these challenges are global, they are especially pronounced in South Africa, influencing not only infrastructure access but also adoption attitudes—thus pointing to the need for the application of behavioural science frameworks, such as COM-B, that are sensitive to context-specific behavioural barriers to, and facilitation of, AI adoption.

A strong argument in the existing literature is that to fully capture the complex interplay between infrastructure access and behavioural intent, especially in contexts marked by inequality, existing IS-oriented technology adoption frameworks may need to be expanded to include behavioural intent (Sohn & Kwon, 2020). One such potential expansion is through incorporation of the COM-B behaviour-change framework. Accordingly, the pilot study discussed in this article explored the extent to which the COM-B framework's constructs, rooted in behavioural science, can be effectively applied to understanding AI adoption, thus complementing insights from established IS-focused technology acceptance models.

The context for the pilot study was the Southern African higher education sector**.** Through piloting a COM-B-focused AI adoption survey in this sector as a test case, we explored the extent to which the COM-B framework could capture barriers to and facilitators of AI adoption in a socially complex setting. Rather than seeking to replace established IS models such as TAM and UTAUT, we sought to determine the extent to which COM-B may offer complementary insights by focusing on behavioural drivers.

The COM-B model was chosen for deployment in this study because it provides a framework for understanding how individual capability (e.g., psychological and physical), motivation (e.g., habits, emotions), and environmental opportunities (e.g., infrastructure and social norms) interact to influence behaviour change (Michie et al., 2011). Like TAM (Davis, 1989), COM-B accounts for both individual and environmental factors. However, unlike TAM, which emphasises cognitive beliefs, such as perceived usefulness and ease of use, COM-B prioritises emotional and automatic motivational drivers, including impulses, emotions, and habits that influence behaviour (Michie et al., 2011; West & Michie, 2021). It is our view that drivers of this nature can be particularly relevant in AI-adoption contexts, because these contexts involve controversial and/or unresolved issues such as algorithmic bias, lack of transparency, misinformation, employment and ethical concerns linked to matters of autonomy and surveillance.

## 2. Study design

### *Identification of AI-adoption barriers and facilitators*

An exploratory literature review was conducted to identify known barriers to, and facilitators of, AI adoption (e.g., infrastructure, training, ethical matters) in South Africa. AI was broadly defined as any digital system or algorithm that supports or automates decision-making in a professional capacity. The healthcare-sector literature was particularly valuable, as it extensively covers behavioural issues that align with the COM-B framework. The literature search was conducted using Google Scholar with keywords such as "artificial intelligence," "machine learning," "implementation science," "barriers to AI implementation/adoption," "healthcare South Africa," and "complication/risk prediction." Boolean operators (AND, OR) were used to refine the searches. Inclusion criteria required articles to be published within the past 10 years and to have a minimum of 10 citations.

A deductive thematic analysis (Braun & Clarke, 2006), guided by the COM-B framework, was applied to the literature-review findings. Using a codebook built from COM-B domain definitions set out by Michie et al. (2011) and supplemented with constructs from the theoretical domains framework (TDF) (Cane et al., 2012), we coded relevant examples of barriers and facilitators according to four COM-B domains:

- psychological capability;
- physical opportunity;
- social opportunity; and
- reflective motivation.

The two remaining domains—automatic motivation, which captures habitual reactions, and physical capability, which captures physical behaviours—were excluded, as they are less relevant to AI adoption in professional contexts where adoption is generally intentional and cognitively mediated. An inductive analysis then grouped these examples into broader themes (see column 3 in Table 1), for example, "accuracy", "data infrastructure", "interpretation", "skills/expertise" and "workflow", which translated sector-specific insights into transferable concepts. These themes informed the first iteration of the survey instrument.

**Table 1: COM-B domains (from Michie et al., 2011), barriers and facilitators, and themes**

| COM-B domains | AI-adoption barriers and facilitators | Themes |
|---|---|---|
| Psychological capability | • Lack of systems integration heightens cognitive demands, limiting individuals' capacity to learn and apply new processes (Ahmed et al., 2020; Leeds et al, 2018; Wiens & Shenoy, 2018)<br>• Additional training intensifies the workload, requiring greater psychological stamina to continually acquire, process, and retain new information (Gesulga et al., 2017; Tan et al., 2022)<br>• Insufficient skills and expertise erode confidence, constraining psychological capability and readiness to adopt new behaviours or technologies (Birkhoff et al., 2021; Cai et al., 2019; Guo & Li, 2018; Gesulga et al., 2017; Tan et al., 2022) | • Accuracy<br>• Data infrastructure<br>• Interpretation<br>• Skills/expertise<br>• Workflow |
| Physical opportunity | • Rural settings limit physical access (Guo & Li, 2018; Owoyemi et al., 2020; Peiffer-Smadja et al., 2020)<br>• Insufficient data availability undermines tool's accuracy (Nelson, 2019; Paiva et al., 2020; Panch et al., 2019; Peiffer-Smadja et al., 2020; Ravi et al., 2016)<br>• Financial demands, from implementation to infrastructure costs, undermine feasibility (Kruse et al., 2016; Owoyemi et al., 2020; Schawalbe et al., 2020)<br>• Privacy, security, and ethical concerns deter uptake (Habehh & Gohel, 2021; Vayena et al., 2018)<br>• Data integration challenges impede seamless operation (Ahmed et al., 2020; Leeds et al., 2018; Wiens & Shenoy, 2018)<br>• Limited specialist availability slows adoption (Birkhoff et al., 2021; Guo & Li, 2018; Paranjape et al., 2019; Wahl et al., 2018)<br>• Supportive resources help overcome resistance rooted in attitudes, culture, and workload concerns (Granja et al., 2018; Jauk et al., 2021; Lambert-Kerzner et al., 2018) | • Access<br>• Accuracy<br>• Costs<br>• Data infrastructure<br>• Ethics and regulation |
| Social opportunity | • Data safety and privacy concerns influence collective acceptance (Bajwa et al., 2021; Habehh & & Gohel, 2021; Vayena et al., 2018)<br>• Clinical practice norms and limited integration foster resistance (Granja et al., 2018; Jauk et al., 2021; Lambert-Kerzner et al., 2018)<br>• Regulatory frameworks, or lack thereof, shaping practice standards (Alexopoulos et al., 2019; Bajwa et al., 2021; Qayyum et al., 2020; O'Sullivan et al., 2019; Owoyemi et al., 2020) | • Context of patient needs<br>• Data infrastructure<br>• Ethics and regulation<br>• Practice norms<br>• Privacy & security<br>• Skills/expertise<br>• Work climate |
| Reflective motivation | • Shared decision-making and patient perspectives influence personal beliefs and willingness to change (Bilimoria et al., 2013; Davenport & Kalakota, 2019; Johnson et al., 2016)<br>• Lack of trustworthy regulations undermines confidence, decreasing motivation to adopt new practices (O'Sullivan et al., 2019; Xiao et al., 2018)<br>• Over-reliance on tools reduces personal agency and sustained motivation (Secinaro et al., 2021) | • *Context of patient needs*<br>• *Ethics and regulation*<br>• *Over-reliance*<br>• *Policy and social infrastructure*<br>• *Practice norms*<br>• *Emotional resistance* |

### *Development of survey instrument*

To develop the survey instrument, we began with an initial pool of 28 open-ended items derived from the thematic analysis (described above) of literature on AI adoption, implementation barriers, and behavioural constructs aligned with the COM-B framework. The survey items were refined through an iterative, consensus-based process by our interdisciplinary team, which brought together expertise in qualitative research, information systems, and implementation science. We prioritised face and content validity, conceptual clarity, and full coverage of the key behavioural domains.

This process involved merging overlapping items, removing redundant or overly narrow items, and revising or splitting unclear items to better reflect distinct concepts. We also adapted the wording to ensure that each item aligned with its intended COM-B domain while still remaining broadly applicable across professional sectors—by, for example, replacing healthcare-specific terms such as "patient" and "clinical work" with more neutral alternatives such as "client" and "job tasks". These revisions preserved the theoretical integrity of the COM-B domains while enhancing the instrument's relevance across various professional contexts, including, but not limited to, higher education.

The AI-adoption barriers and facilitators identified in the literature were then mapped to the COM-B domains to generate 16 statements that could be surveyed via a 10-point Likert-type scale, with the scale measuring level of agreement with the statement (with 1 being the lowest level of agreement). The final 16 survey items used in the survey (see Table 2 below) explored factors influencing AI adoption in professional settings in terms of four COM-B domains drawn from Michie et al. (2011): psychological capability, physical opportunity, social opportunity, and reflective motivation.

- *Psychological capability* refers to an individual's perceived knowledge, skills, and cognitive abilities. In the context of AI, this includes understanding how to interpret AI outputs and operate AI tools effectively.
- *Physical opportunity* refers to environmental resources, time, and infrastructure. In the context of AI, this includes adequate infrastructure for data integration, data sharing, and privacy safeguards.
- *Social opportunity* refers to cultural norms, social influences, and peer support. In the context of AI, this includes clinical practice norms, workplace climate, regulatory frameworks, and best practices.
- *Reflective motivation* captures beliefs, attitudes, and intentions. In the context of AI, this includes trust in AI and ethical concerns.

**Table 2: The 16 COM-B-aligned statements used in the survey**

| COM-B domain(s) (from Michie et al., 2011) | Survey statement | Potential facilitator or barrier |
|---|---|---|
| Reflective motivation | I am concerned about relying too much on AI tools for my professional decisions. | Barrier |
| Psychological capability | I have adequate skills to run AI tools in my industry. | Facilitator |
| Psychological capability & reflective motivation | When using AI tools in my industry, I understand and am confident in the results and/or output. | Facilitator |
| Psychological capability & social opportunity | I am prepared to address my clients' ethical issues regarding AI tools in my decision-making. | Facilitator |
| Physical opportunity | My workplace has adequate technological infrastructure to effectively use AI tools. | Facilitator |
| Physical opportunity | Our current computer systems easily integrate AI tools. | Facilitator |
| Physical opportunity | My workplace has adequate support systems to effectively implement AI tools. | Facilitator |
| Physical opportunity | Our AI tools comply with regulation and privacy laws. | Facilitator |
| Physical opportunity | I can integrate AI tools into my job tasks with minimal effort and time. | Facilitator |
| Physical opportunity | The costs of infrastructure and resources limit our ability to use AI tools. | Barrier |

| | | |
|---|---|---|
| Reflective motivation | AI tools benefit our clients. | Facilitator |
| Reflective motivation | Our AI tools are accurate enough to inform our professional decisions. | Facilitator |
| Reflective motivation | The precision of AI tools impacts my willingness to use AI tools for professional decisions. | Barrier |
| Reflective motivation & social opportunity | We are concerned that clients may have ethical concerns about our use of AI tools in decision-making. | Barrier |
| Social opportunity | Integrating AI tools aligns with our industry's best practices and standards. | Facilitator |
| Social opportunity | Our workplace culture supports and rewards innovation. | Facilitator |

### *Survey administration*

In November 2024, the pilot survey was electronically distributed via Qualtrics, an online survey platform that enables secure distribution and collection of questionnaire responses (Qualtrics, 2024)[1], to 100 higher education employees affiliated with the Southern African Association for Institutional Research (SAAIR)[2], a regional professional body comprising university staff and faculty. SAAIR membership spans a wide range of institutions (e.g., research-intensive, teaching-focused, rural, and urban universities) across the Southern African region. The target respondents worked primarily in academic planning, institutional research, and policy roles, and had all previously expressed an interest in AI. The survey was administered shortly after a SAAIR conference forum focused on the impact of generative AI in higher education. As such, the potential respondents were likely to have a working knowledge of AI and a shared context for interpreting the survey questions. Of the 100 individuals contacted, 32 responded, yielding a 32% response rate. The survey had five demographic questions, covering age, job sector, job title, years of experience, and country of origin, followed by the 16 COM-B-framed items that respondents scored via a 10-point Likert-type scale. The scale ranged from 1 = strongly disagree to 10 = strongly agree.

### *Data analysis*

The dataset generated by the survey responses on the Qualtrics platform was analysed using median scores, interquartile ranges (IQRs), and coefficient of quartile variations (CQVs). Medians highlighted central tendencies, with higher values indicating stronger agreement with the survey statement. Interquartile ranges (IQRs) were used to describe the spread of the data, indicating the range within which the middle 50% of responses fell. The coefficient of quartile variation (CQV) assessed relative variability around the median, with higher CQV values indicating greater relative dispersion within the data. Medians of 7 or above (on the 1–10 scale) were interpreted as indicating strong agreement with the survey statement. Medians between 5 and 6, near the midpoint of the scale, indicated neutral or mixed levels of agreement. Medians below 5 signified disagreement. CQV values below 0.4 indicated a strong consensus among respondents, while values above 0.6 suggested divergent views and lower consensus.

## 3. Results and discussion

### *Respondent demographics*

As shown in Table 3, the respondents' years of experience in their current positions ranged between less than a year and more than 20 years, with the largest subgroup (7 respondents) having 11 to 15 years of experience. The ages of the respondents ranged between 25 and 65-plus, with the largest numbers of participants being in the 35–44 and 45–54 age bands. Respondents held diverse positions, with the role of programme director or manager being the most common (9 respondents), followed by planner or administrator (5 respondents), and teaching, learning or curriculum specialist (5 respondents), data analyst or administrator (4 respondents), researcher or consultant (4 respondents), quality assurance officer or consultant (3 respondents) and professor or lecturer (2 respondents).

1 https://www.qualtrics.com
2 https://www.saair-web.co.za

**Table 3: Respondent demographics (N=32)**

| Years of experience in current position | N (%) |
|---|---|
| Less than 1 year | 5 (15.6) |
| 1 to 2 years | 6 (18.8) |
| 3 to 5 years | 6 (18.8) |
| 6 to 10 | 3 (9.4) |
| 11 to 15 | 7 (21.9) |
| 16 to 20 | 1 (3.1) |
| More than 20 | 4 (12.5) |
| | |
| **Age** | **N (%)** |
| 25 to 34 | 4 (12.5) |
| 35 to 44 | 9 (28.1) |
| 45 to 54 | 9 (28.1) |
| 55 to 64 | 7 (21.9) |
| 65-plus | 3 (9.4) |
| | |
| **Position** | **N (%)** |
| Programme director or manager | 9 (28.1) |
| Planner or administrator | 5 (15.6) |
| Teaching, learning, or curriculum specialist | 5 (15.6) |
| Data analyst or administrator | 4 (12.5) |
| Researcher or consultant | 4 (12.5) |
| Quality assurance officer or consultant | 3 (9.4) |
| Professor or lecturer | 2 (6.3) |

### *Findings from COM-B-aligned survey items*

*Potential facilitators of AI adoption*

Median scores for potential facilitators on the 10-point Likert-type scale ranged from 5 to 7.5 (Table 4). The highest median score (7.5) indicated agreement on the presence of adequate technological infrastructure for using AI tools. Three other potential facilitators received strong median scores (7): preparedness to address clients' ethical issues regarding AI tools in the respondents' decision-making; the ability of the respondents' computer systems to integrate AI tools; and the benefit that respondents felt AI offered to their clients.

The lowest median scores (5) were observed for three factors: having adequate workplace support systems to effectively implement AI tools; ensuring AI tools comply with regulations and privacy laws; and confidence that AI tools are accurate enough to inform professional decisions. CQVs ranged from 0.17 to 0.73. The highest consensus (CQV = 0.17) pertained to the presence of adequate technological infrastructure, while the lowest consensus (CQV = 0.73) related to beliefs about workplace culture supporting innovation.

Through examining medians and CQVs simultaneously, it was found that three of the four items with high medians also reflected strong consensus, as indicated by CQVs below 0.4. These were: the presence of adequate technological infrastructure for using AI tools (median = 7.5, CQV = 0.17); preparedness to respond to clients' ethical concerns (median = 7, CQV = 0.32); and the benefit AI tools provide to clients (median = 7, CQV = 0.29). There was less consensus on the ease of respondents' computer systems integrating AI tools (median = 7, CQV = 0.43).

**Table 4: Findings on potential facilitators of AI adoption**

| COM-B domain(s) | Survey statement *(1=strongly disagree to 10=strongly agree)* | Lowest score | Highest score | Median score | IQR | CQV | Variability |
|---|---|---|---|---|---|---|---|
| Physical opportunity | My workplace has adequate technological infrastructure to effectively use AI tools. | 1 | 10 | 7.5 | 1.25 | 0.17 | low |
| Psychological capability & social opportunity | I am prepared to address my clients' ethical issues regarding AI tools in my decision-making. | 2 | 10 | 7 | 2.25 | 0.32 | medium |
| Physical opportunity | Our current computer systems easily integrate AI tools. | 2 | 10 | 7 | 3 | 0.43 | medium |
| Reflective motivation | AI tools benefit our clients. | 2 | 10 | 7 | 2 | 0.29 | medium |
| Social opportunity | Integrating AI tools aligns with our industry's best practices and standards. | 3 | 10 | 6.5 | 3 | 0.46 | medium |
| Psychological capability | I have adequate skills to run AI tools in my industry. | 1 | 10 | 6 | 3 | 0.5 | high |
| Psychological capability & reflective motivation | When using AI tools in my industry, I understand and am confident in the results and/or output. | 1 | 10 | 6 | 3.25 | 0.54 | medium |
| Physical opportunity | I can integrate AI tools into my job tasks with minimal effort and time. | 1 | 10 | 6 | 4 | 0.67 | medium |
| Social opportunity | Our workplace culture supports and rewards innovation. | 2 | 10 | 5.5 | 4 | 0.73 | high |
| Physical opportunity | My workplace has adequate support systems to effectively implement AI tools. | 1 | 9 | 5 | 3 | 0.6 | high |
| Physical opportunity | Our AI tools comply with regulation and privacy laws. | 1 | 10 | 5 | 3 | 0.6 | high |
| Reflective motivation | Our AI tools are accurate enough to inform our professional decisions. | 1 | 9 | 5 | 2 | 0.4 | medium |

*Potential barriers to AI adoption*

Median scores for potential barriers on the 10-point Likert-type scale ranged from 6 to 7 (Table 5). The higher median score (7) indicated agreement on three potential barriers: concerns about overreliance on AI for professional decisions; the uncertain precision of AI tools affecting willingness to use them; and clients' ethical concerns about using AI in decision-making. The lower median score (6) was observed for the barrier

posed by costs of infrastructure and resources. CQVs ranged from 0.29 to 0.71. The highest consensus (CQV = 0.29) pertained to concern about clients' ethical concerns, while the lowest consensus (CQV = 0.71) related to concerns about overreliance on AI and about the costs of infrastructure and resources.

Through examining medians and CQVs together, we were able to identify one potential barrier with both a high median and a strong consensus (a CQV below 0.4). That potential barrier was that clients may have ethical concerns about the use of AI tools in decision-making (median = 7; CQV = 0.29). There was less consensus about two other potential barriers that had high median scores: overreliance on AI (median = 7; CQV = 0.71) and costs of infrastructure and resources (median = 6; CQV = 0.73).

**Table 5: Findings on potential barriers to AI adoption**

| COM-B domain(s) | Survey statement (1=strongly disagree to 10=strongly agree) | Lowest score | Highest score | Median score | IQR | CQV | Variability |
|---|---|---|---|---|---|---|---|
| Reflective motivation | I am concerned about relying too much on AI tools for my professional decisions. | 1 | 10 | 7 | 5 | 0.71 | medium |
| Reflective motivation | The precision of AI tools impacts my willingness to use AI tools for professional decisions. | 2 | 10 | 7 | 3 | 0.43 | medium |
| Reflective motivation & social opportunity | We are concerned that clients may have ethical concerns about our use of AI tools in decision making. | 2 | 10 | 7 | 2 | 0.29 | high |
| Physical opportunity | The costs of infrastructure and resources limit our ability to use AI tools. | 2 | 10 | 6 | 4.25 | 0.71 | high |

## 4. Conclusions and limitations

The results of this pilot study, as set out above, suggest that the COM-B model offers a potentially useful behaviourally grounded lens for evaluating AI adoption, thus potentially complementing traditional IS models such as TAM and UTAUT. Deployment of the COM-B model has the potential to contribute to the understanding of technology adoption's behavioural-intention construct—a construct that, in existing technology-adoption frameworks, is often limited to variables such as ease of use and perceived usefulness. In the evolving landscape of AI, the application of the COM-B model in adoption research has the potential to help assess readiness by identifying gaps in capability, opportunity, and motivation.

Because it was a pilot exercise, this study had several limitations. The small sample size (n = 33), and narrow focus on a particular grouping of Southern African higher education professionals, restricted generalisability. The sample was also not large enough to support formal psychometric validation. While COM-B is a widely validated framework, future research should assess the reliability and validity of this specific model in the AI adoption context via larger, more diverse samples. Also, the survey did not collect information on which AI tools respondents used or how they defined AI, which may have introduced variability in interpretation. Additionally, some education-specific or sectoral nuances may not have been fully captured. We recommend that future studies include items capturing respondents' AI usage and definitions and incorporate sector-specific validation. We also acknowledge that only a few items were used to assess each COM-B construct, which may have limited internal consistency. Also, the use of a 10-point Likert-type scale, despite offering granularity, may have introduced ceiling and/or floor effects.

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**Competing interests declaration**
The authors have no competing interests to declare.

**Data availability statement**

The data supporting the findings of this study is available upon written request to the first-listed author at : pattersonmar@umkc.edu

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**Authors' contributions**

M.E.P: Conceptualisation, methodology, data collection and analysis, validation, data curation, writing and revisions of the manuscript, student supervision, project management, project leadership activities. J.B.: Conceptualisation, methodology, data collection and analysis, validation, data curation, manuscript revisions, student supervision.

I.C.: Conceptualisation, methodology, validation, manuscript revisions.

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