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# People, data and decisions: Overcoming individual barriers to data-driven practice in South African universities



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**Background:** Data-driven decision-making (D3M) has become essential for enhancing efficiency, accountability and student success in higher education institutions (HEIs). Yet, South African universities continue to face challenges in adopting D3M, particularly because of individual-level barriers among staff who engage with data systems.

**Objectives:** This study investigates individual barriers to D3M adoption among decision-makers in South African HEIs and proposes strategies to build capacity for effective and sustainable implementation.

**Method:** A qualitative case study approach was employed, involving 24 semi-structured interviews conducted with senior managers, data specialists and academic staff at the University of the Western Cape. Thematic analysis was utilised to identify personal and contextual factors shaping D3M engagement.

**Results:** The study recommends targeted capacity-building interventions, including awareness campaigns, diagnostic skills assessments and multi-tiered training programmes that integrate confidence-building and peer mentoring. Institutions should implement gradual, age-sensitive rollouts and appoint D3M champions to promote adoption by demonstrating success.

**Conclusion:** By foregrounding individual-level dynamics, the study extends the unified theory of acceptance and use of technology 2 (UTAUT2) and self-efficacy theory to the South African higher education context. It contributes actionable strategies for cultivating data-literate, confident and digitally empowered academic communities that support institutional transformation.

**Contribution:** This research fills a gap in understanding personal-level barriers to D3M adoption in the under-researched South African higher education context. It contributes actionable insights for higher education leaders and policymakers.

**Keywords:** data-driven decision-making; data culture; individual factors; self-efficacy; higher education institutions; technology adoption; the unified theory of acceptance and use of technology 2.

## Introduction

South African higher education institutions (HEIs) operate within a context of persistent resource constraints, widening inequalities and growing demands for accountability and improved student outcomes. In response to these pressures, data-driven decision-making (D3M) has emerged as a strategic approach to enhance institutional effectiveness and support student success. Data-driven decision-making is the collection, analysis, and use of data to guide and support decisions (Custer et al. 2018). This process involves using data and analytics tools and techniques to guide strategic decisions aligned with business objectives. Data-driven decision-making enables universities to make informed choices about resource allocation, identify at-risk students early, and evaluate programme performance based on evidence rather than intuition (Ashaari et al. 2021).

For South African universities, which serve diverse and often vulnerable student populations, effective data use is crucial for advancing national development goals such as reducing inequality, promoting inclusion and building a capable state (Selowa, Ilorah & Mokwena 2022). Despite the recognised potential of D3M, adoption remains uneven. Many institutions still rely

on fragmented systems and ad hoc practices that limit the use of analytics for planning and monitoring. Building capacity for D3M among university staff, therefore, holds significant social value: it enhances institutional responsiveness, supports evidence-based management, and contributes to a more equitable and sustainable higher-education system.

While international research has highlighted technological and organisational enablers of D3M (Hakkal & Ait Lahcen 2022; Tsai et al. 2020), relatively little attention has been given to the individual-level factors that influence adoption – particularly within developing-country contexts. Studies in South Africa have mostly examined data governance and infrastructure readiness but seldom explored how academic and administrative staff's beliefs, confidence and digital literacy affect their engagement with data systems (Cele 2021; Van Dyk & Van Belle 2019). This limited focus leaves a critical knowledge gap concerning the human capabilities that enable sustainable institutional transformation through data use.

The scientific contribution of this study lies in addressing this gap by analysing the personal and behavioural barriers that hinder D3M adoption. It advances existing knowledge by demonstrating how psychological and contextual factors intersect to shape adoption outcomes, thereby extending current technology adoption theories to the South African HEI environment.

The study draws on two complementary theories: the unified theory of acceptance and use of technology 2 (UTAUT2) (Venkatesh, Thong & Xu 2016) and Bandura's (1997) self-efficacy theory. Unified theory of acceptance and use of technology 2 is a consolidated behavioural theory that explains technology adoption through expectancy-value beliefs, social influence mechanisms, and facilitating conditions, predicting behavioural intention and use behaviour (Venkatesh et al. 2016). It extends earlier technology acceptance models by incorporating hedonic motivation, habit, and moderating demographic factors. Self-efficacy refers to individuals' beliefs in their capabilities to organise and execute courses of action required to manage prospective situations (Bandura 1997). In technology contexts, self-efficacy determines persistence, resilience in the face of difficulty and willingness to experiment with new systems. By integrating these frameworks, the study conceptualises D3M adoption as a function of both technological perceptions and personal confidence, mediated by institutional support and training opportunities.

This study aimed to investigate individual barriers to D3M adoption among staff members in South African HEIs and to identify strategies to mitigate them. The objectives were:

- To identify individual-level factors that hinder D3M adoption in South African HEIs.
- To examine how self-efficacy and perceptions of technology shape behavioural intentions to engage with D3M.
- To propose evidence-based strategies to mitigate identified barriers.

## Literature review

Data-driven decision-making has gained increasing attention in higher education as a mechanism to enhance institutional effectiveness, student success and evidence-based management. Globally, D3M adoption has been associated with improved accountability, predictive analytics for student retention and optimised resource allocation (Ashaari et al. 2021). However, in many South African HEIs, the potential of D3M remains unrealised. Cele (2021) highlights infrastructural and governance constraints that limit the effective analytics use, while Van Dyk and Van Belle (2019) emphasise the role of organisational readiness and digital transformation capacity. Together, these studies point to a complex interaction of technological, organisational and human factors that inhibit adoption. This literature review critically explores individual-level determinants of D3M adoption – perceptions and attitudes, digital literacy, self-efficacy, prior experience and cultural beliefs – through the lenses of the UTAUT2 and self-efficacy theory.

### Perceptions and attitudes towards data-driven decision-making

Perceptions and attitudes play a foundational role in technology adoption. Within the UTAUT2 model, constructs such as performance expectancy, effort expectancy and social influence are key predictors of behavioural intention (Venkatesh et al. 2016). Studies indicate that when individuals perceive D3M tools as useful, easy to use, and socially endorsed, adoption is more likely (Lai 2017; Venkatesh et al. 2003). Conversely, when tools are viewed as complex or irrelevant, staff exhibit resistance, anxiety or superficial engagement (Farjon, Smits & Voogt 2019).

In higher education, these perceptions are influenced by prior exposure to technology, disciplinary culture and demographic variables such as age and experience (Tamilmani, Rana & Dwivedi 2020; Van Dyk & Van Belle 2019). For example, academics in quantitative fields often exhibit stronger positive attitudes towards data use than those in the humanities, where interpretive and qualitative traditions dominate (Sarkar et al. 2021). This highlights that attitudes towards D3M are not merely personal but are also shaped by epistemological orientations and professional identity.

Despite growing interest, most research emphasises the 'what' of attitudes rather than the 'why'. Few studies critically interrogate how institutional culture and reward systems reinforce or weaken staff motivation to engage with D3M. South African HEIs, in particular, continue to grapple with hierarchical decision-making cultures and limited feedback loops, which reduce staff agency in shaping data practices (Cele 2021). Understanding these perceptual barriers is crucial for cultivating a positive data culture that extends beyond compliance to genuine professional empowerment.

## Digital literacy and knowledge gaps

Digital and data literacy underpin effective D3M in higher education. This capability extends beyond technical skills (e.g. analysing, interpreting and communicating data) to include the capacity to apply evidence in ways that meaningfully shape institutional decisions and everyday practice (Georgopoulou et al. 2025). At the organisational level, developing a data-driven culture (DDC) requires more than tools and dashboards; it involves shared norms, governance and alignment across roles so that data use becomes embedded in decision processes rather than remaining an isolated technical function (Barbala, Hanssen & Sporsem 2024). The absence of these skills among academic and administrative staff has emerged as a persistent barrier to adoption in both developed and developing contexts (Khan, Usman & Moinuddin 2024).

In South Africa, this challenge is compounded by uneven access to professional development and infrastructure. While some universities have developed analytics units or dashboards, others still rely on fragmented reporting systems with limited user training (Selowa et al. 2022). Staff in non-technical disciplines are particularly disadvantaged because of limited exposure to data-intensive methods during their academic training. As a result, D3M capacity often resides in a small circle of institutional experts rather than being diffused across the academic community.

O'Brien et al. (2022) found that informal, on-the-job learning tends to produce shallow engagement with D3M tools, whereas structured training programmes foster deeper understanding and sustained use. Yet many South African HEIs lack standardised data literacy curricula or continuing professional development frameworks in this domain. Consequently, digital skills deficits persist, reinforcing dependence on IT specialists and diminishing end users' ownership of evidence-based decision-making.

## Self-efficacy and technology anxiety

Self-efficacy, one's belief in their ability to perform specific tasks, plays a central role in explaining technology adoption behaviour (Bandura 1997). Within D3M, self-efficacy affects whether individuals feel capable of interpreting and acting upon data outputs. Research indicates that even trained users may avoid analytics tools if they doubt their ability to use them correctly (Nguyen et al. 2020; Sarkar et al. 2021). This phenomenon, termed technology anxiety, often manifests as reluctance to engage with new platforms or datasets for fear of making mistakes or being judged as incompetent.

Low self-efficacy in South African HEIs is often rooted in historical inequities in digital access and training, particularly among older academics or those educated before the widespread integration of technology into teaching and administration (Moyo 2021). Confidence deficits are further exacerbated when institutions fail to provide accessible technical support or mentorship. Shank (2023) emphasises that continuous scaffolding through help desks, data champions or peer mentoring can mitigate this anxiety by fostering a culture of shared learning. Thus, self-efficacy operates not in isolation but within an institutional ecosystem that either empowers or discourages digital engagement.

## Prior experience with technology

Previous experiences with technology strongly influence readiness for future adoption. Unified theory of acceptance and use of technology 2 identifies habit and facilitating conditions as critical predictors shaped by users' prior encounters with systems (Venkatesh et al. 2016). Negative experiences, such as unreliable systems, poor usability or lack of demonstrable benefit, tend to foster cynicism toward new initiatives (Kokkinou, Mandemakers & Mitas 2024). Conversely, positive experiences with well-supported, user-friendly systems build trust and willingness to experiment (Chomunorwa & Van den Berg 2023).

Participatory approaches that involve staff in the design and piloting of data systems have been shown to enhance ownership and motivation (Chomunorwa, Van den Berg & Jantjies 2023). This aligns with social influence constructs in UTAUT2, where peer collaboration and visible success stories drive broader adoption. Phased rollouts that prioritise consultation and visible benefits may therefore help South African HEIs overcome resistance and foster sustainable D3M cultures.

## Cultural and ideological beliefs in higher education

Cultural and ideological dimensions remain underexplored in D3M research. Some academics perceive data analytics as a managerialist intrusion that commodifies education or undermines academic autonomy (Komljenovic 2022). When metrics are used for surveillance rather than developmental purposes, data initiatives risk alienating the very individuals expected to adopt them. Tsai and Gašević (2017) caution that successful implementation depends on cultivating trust and transparency about how data are collected, analysed, and used.

Within South Africa's transforming higher education landscape, such ideological concerns are amplified by historical mistrust of top-down management and fears of decontextualised performance metrics (Czerniewicz 2018). Addressing these issues requires ethical and participatory data governance, in which staff co-create indicators and maintain agency over their interpretation. Cultivating a culture of care-based data use, in which analytics support teaching and learning rather than surveillance, can help bridge the gap between policy ambition and practical acceptance. The notion of DDC provides a useful conceptual anchor for understanding these dynamics. Gupta and George (2016:1053) define DDC as 'the extent to

which organisational members (including top-level executives, middle-managers and lower-level employees) make decisions based on the insights extracted from data'. This definition emphasises that D3M is not merely a technological capability but a collective behavioural orientation embedded across organisational hierarchies. In higher education contexts, cultivating DDC therefore requires attention not only to infrastructure and analytics tools, but also to individual beliefs, confidence and everyday decision-making practices.

The reviewed literature underscores that while D3M adoption has been widely studied from organisational and technological perspectives, the individual dimension remains under-theorised and under-investigated, particularly in the global south. Research consistently shows that perceptions, skills, self-efficacy and cultural beliefs interact to shape behavioural intention, yet these relationships are seldom examined holistically. Furthermore, little is known about how these psychological and contextual factors manifest in resource-constrained, postcolonial higher education systems such as those in South Africa.

This study addresses that gap by integrating UTAUT2 and self-efficacy theory to provide a nuanced understanding of how individual characteristics and institutional contexts jointly influence D3M adoption. By foregrounding the human dimension of data culture, it contributes both theoretical and practical insights into building digitally confident, data-literate and empowered academic communities in South African HEIs.

# Research methodology

## Research design

This study adopted a qualitative exploratory case study design to investigate individual-level barriers to D3M adoption within a South African HEI. A qualitative approach was appropriate because the research sought to understand participants' life experiences, perceptions and meanings associated with D3M, rather than to test predetermined hypotheses (Creswell & Poth 2018). The case study design allowed for an in-depth, context-specific examination of behavioural, institutional and cultural factors that shape D3M practices (Yin 2009).

The selected HEI, located in the Western Cape, was chosen for its diverse academic profile and active participation in institutional transformation initiatives, which provided a relevant environment for exploring individual readiness and challenges related to data adoption.

## Research setting and context

South African HEIs operate within a complex landscape shaped by historical inequalities, variable digital infrastructure and increasing accountability demands. The chosen institution reflects these broader national dynamics, where D3M initiatives coexist with uneven digital literacy levels and differing organisational cultures across faculties. This contextual diversity made it an ideal setting to explore the micro-level human factors influencing D3M adoption.

## Participants and sampling

A purposive sampling strategy was employed to ensure inclusion of participants directly involved in decision-making or data use within the institution. Twenty-four participants were selected across three categories:

- Senior management and executives (e.g. deans, directors, heads of department) responsible for institutional strategy and performance monitoring.
- Academic staff who engage with data for teaching, learning and student support purposes.
- Administrative and technical staff (e.g. data analysts, planners, IT personnel) supporting data collection, analysis and reporting processes.

Participants were recruited through departmental communications and referrals, based on their involvement in D3M-related processes. Diversity in role, gender, experience and disciplinary background was prioritised to capture multiple perspectives. Sampling continued until data saturation was achieved, when no new themes or insights emerged (Guest, Namey & Chen 2020). A summary of participant demographics is provided in Table 1.

## Data collection

Data were collected through semi-structured interviews, which allowed for flexibility in exploring participants' individual experiences and perspectives while ensuring consistency across core themes. The interview guide was informed by the theoretical constructs of the UTAUT2 and self-efficacy theory, as well as insights from the literature review.

Interview questions covered five broad areas:

- Understanding and awareness of D3M concepts and tools.
- Experiences with data use in teaching, administration or planning.
- Perceived skills and confidence in engaging with data.
- Institutional support, training and barriers.
- Personal attitudes, motivations and fears regarding data-driven practices.

Interviews were conducted via Microsoft Teams or face-to-face, depending on participant preference and COVID-19 protocols. Each session lasted approximately 45–60 min, was audio-recorded with consent, and subsequently transcribed verbatim. Field notes were also maintained to capture contextual observations and researcher reflections.

## Data analysis

Data were analysed thematically using the six-phase framework proposed by Braun and Clarke (2012): (1)

**TABLE 1:** Participant demographics.

| Participant code | Age group (years) | Gender | Qualification | Function | Experience (years) |
|---|---|---|---|---|---|
| P1 | 50–59 | Male | Doctorate | Academic | 28 |
| P2 | 30–34 | Male | Doctorate | Academic | 4 |
| P3 | 40–49 | Female | Doctorate | Management | 7 |
| P4 | 40–49 | Male | Undergraduate | Support | 13 |
| P5 | 25–29 | Female | Diploma | Support | 6 |
| P6 | 50–59 | Female | Doctorate | Management | 16 |
| P7 | 50–59 | Male | Masters | Academic | 29 |
| P8 | 50–59 | Female | Honours | Data specialist | 34 |
| P9 | 40–49 | Female | Doctorate | Academic | 9 |
| P10 | 50–59 | Male | Honours | Data specialist | 12 |
| P11 | 35–39 | Male | Doctorate | Academic | 11 |
| P12 | 40–49 | Female | Doctorate | Management | 8 |
| P13 | 35–39 | Female | Diploma | Support | 13 |
| P14 | 40–49 | Female | Masters | Data specialist | 8 |
| P15 | 25–29 | Female | Masters | Data specialist | 4 |
| P16 | 30–34 | Female | Masters | Academic | 7 |
| P17 | 40–49 | Male | Doctorate | Data specialist | 16 |
| P18 | 25–29 | Female | Honours | Data specialist | 6 |
| P19 | 35–39 | Female | Undergraduate | Data specialist | 12 |
| P20 | 50–59 | Male | Undergraduate | Support | 23 |
| P21 | 40–49 | Male | Undergraduate | Data specialist | 5 |
| P22 | 35–39 | Female | Masters | Academic | 13 |
| P23 | 50–59 | Male | Doctorate | Management | 9 |
| P24 | 35–39 | Male | Masters | Academic | 6 |

familiarisation with the data; (2) generating initial codes; (3) searching for themes; (4) reviewing themes; (5) defining and naming themes; and (6) producing the report. The analysis was primarily inductive, allowing themes to emerge from the data while remaining informed by theoretical constructs from UTAUT2 (e.g. effort expectancy, social influence, facilitating conditions) and self-efficacy theory.

Transcripts were read and re-read for meaning units, which were coded manually using Microsoft Excel to maintain transparency and traceability. To enhance analytical rigour, peer debriefing sessions were held with two research colleagues to discuss coding patterns and refine theme definitions. Reflexive journaling helped the researcher maintain awareness of potential biases during interpretation.

### Ensuring trustworthiness

The study adhered to the criteria for qualitative trustworthiness proposed by Lincoln and Guba (1985):

- Credibility was ensured through prolonged engagement with participants, triangulation of data sources (academic, administrative and managerial staff) and peer debriefing.
- Dependability was maintained by creating an audit trail documenting the research process, from interview protocols to coding decisions.
- Confirmability was supported by reflexive journaling and the inclusion of direct quotations to illustrate participants' voices.
- Transferability was enhanced through rich contextual descriptions of the research setting, allowing readers to judge the applicability of findings to other HEIs.

### Ethical considerations

Ethical clearance to conduct this study was obtained from the University of the Western Cape Human and Social Sciences Research Ethics Committee (HSSREC) (Ref. No. HS21/9/11).

## Results and discussion

This qualitative study explored how individual and contextual factors influence the adoption of D3M within a South African HEI. The analysis, guided by UTAUT2 and self-efficacy theory, revealed that the challenge is less about technology access and more about human readiness, confidence and culture. Four themes emerged: limited awareness and understanding of D3M; uneven digital literacy and low confidence; self-efficacy and technology anxiety; and cultural perceptions and institutional support.

### Awareness and understanding of data-driven decision-making

Findings reveal that limited awareness and misconceptions about D3M are pervasive. Limited awareness of D3M emerged as a barrier to adoption among participants. The majority of participants (15 of 19) demonstrated limited understanding of what D3M entails and how it could benefit their work. Many participants associated data use primarily with compliance or reporting rather than with decision enhancement. However, participants expressed interest in adopting D3M if they had better knowledge about its applications and benefits:

> 'I would want to adopt D3M if I knew more about it … I think it would be great to have a system that helps with decision-making as it would make my work easier.' (P5, 25–29 years, Female)

> 'My wildest dream is to have a system that has a dashboard, where I can see all the trends and patterns, and suggested interventions.' (P12, 40–49 years, Female)

> 'Imagine not having to deal with all this manually. If we can have a system whereby you simply capture all the information, and it analyses and gives you possible solutions. That will make life easier!' (P4, 40–49 years, Male)

This finding reveals that awareness campaigns and educational initiatives are crucial first steps in promoting D3M adoption. The lack of understanding creates a barrier that prevents stakeholders from recognising the potential value of data-driven approaches. Recent systematic evidence shows that organisational readiness, leadership commitment and staff digital competence are central to analytics adoption in HEIs (Márquez et al. 2024). Within this case, low awareness restricted participants' ability to perceive practical benefits, weakening performance expectancy, while uncertainty about technical complexity heightened effort expectancy, both of which are critical constructs in UTAUT2 (Venkatesh et al. 2016).

The consistency of these patterns across studies underscores that skills and conceptual clarity must form the foundation of any D3M implementation strategy. Staff need to see how data directly improves their teaching, planning or resource allocation decisions before meaningful adoption can occur.

## Uneven digital literacy and confidence levels

The study found uneven levels of digital and data literacy across faculties; participants described feeling underprepared to work with dashboards, visualisation tools or analytics systems. A significant proportion of participants (12 of 19) reported lacking the necessary skills and knowledge to integrate D3M tools and techniques into their decision-making processes:

> 'Every now and then, there is something new which needs training. It's too much, and I can't keep up. It is frustrating.' (P22, 35–39 years, Female)

> 'Most people lack skills, and that makes it difficult. Some are just not interested in training. They prefer to stay in their comfort zones.' (P14, 40–49 years, Female)

These gaps reflect structural inequities in professional development, as some disciplines have historically emphasised data competence while others have not (Cele 2021). Consistent with O'Brien et al. (2022), once-off training sessions produced limited impact; participants called for continuous, contextualised learning opportunities.

Within UTAUT2, these findings link to facilitating conditions, as inadequate support structures and limited hands-on exposure hinder skill development and increase cognitive load. Bridging these divides, therefore, requires systematic, tiered training that integrates both technical capability and confidence-building.

## Self-efficacy and technology anxiety

Self-efficacy emerged as a decisive factor shaping D3M engagement. Participants with low self-efficacy expressed anxiety and reluctance to engage with data-driven approaches, while those with higher confidence levels showed greater willingness to adopt D3M. Participants frequently described low confidence and anxiety about 'getting the data wrong':

> 'Data is available, and too much of it. I struggle to decide which data to use and for what purpose. Some of these things require specialists. Some of us do not know how to use it. If someone can analyse and tell me what to do, I can change the way I do it [*make decisions*].' (P4, 40–49 years, Male)

Others reported that confidence grew over time with more practice and experience:

> 'During training, it appeared simple. When I tried alone in my office, I struggled the first time. With practice, it gets simple. Now I am confident.' (P7, 50–59 years, Male)

Self-efficacy emerged as a critical psychological factor that mediates the relationship between skills training and actual technology adoption. Participants with low self-efficacy remained hesitant even after receiving training, suggesting that confidence-building measures are essential components of D3M implementation strategies. Drawing on Bandura's (1997) conceptualisation of mastery and persistence, Nguyen et al. (2020) show that perceived competence predicts sustained engagement with digital tools. Schildkamp et al. (2017) similarly noted that staff who see themselves as data-competent become advocates for evidence-based practice.

Low self-efficacy thus operates as a psychological barrier even when infrastructure is available. Building it requires incremental exposure, supportive mentoring and recognition of small successes, conditions that reduce anxiety and enhance perceived mastery.

## Cultural perceptions and institutional resistance

The data revealed subtle but pervasive cultural resistance to D3M. The resistance is rooted in the prevailing institutional culture, where individuals use approaches they are comfortable with, regardless of the implications for student experiences and institutional performance. This cultural resistance appears to stem from comfort with existing practices and scepticism about the benefits of data-driven approaches, especially when they are not actively encouraged by the institution. As mentioned by participants:

> 'Yes, I know it is important to make evidence-based decisions, but I don't think there is an effort to encourage that.' (P7, 50–59 years, Male)

> 'Why not stick to what works?' (P22, 35–39 years, Female)

This echoes patterns in HEIs globally, where institutional culture and peer norms shape technology adoption

(Komljenovic 2022; Tsai & Gašević 2017). In this case, data use was often viewed as an external managerial imposition rather than a collaborative improvement process. Such perceptions reflect negative facilitating conditions and low social influence (UTAUT2), as established cultural norms normalise non-data-based decision-making.

Changing this requires long-term cultural transformation, embedding D3M into everyday routines and rewarding data-informed initiatives. As several participants noted, motivation increases when data use is linked to meaningful feedback and visible institutional benefits.

## Contextualising unified theory of acceptance and use of technology 2 constructs and technology adoption

The findings of this study align closely with UTAUT2 and self-efficacy theory, providing a coherent framework for interpreting behavioural intention and actual use of D3M practices among academic and administrative staff.

Within the UTAUT2 model, several constructs are reflected in participants' experiences. The Effort Expectancy and Performance Expectancy dimensions are evident in the way limited awareness and perceived complexity of D3M tools reduce motivation and perceived usefulness. Participants who lacked an understanding of how data-driven practices could improve their work displayed low performance expectancy, as they were unable to visualise practical benefits while also perceiving D3M systems as difficult to master, indicating high effort expectancy. These perceptions weaken behavioural intention and reduce engagement. Conversely, systematic awareness and training programmes can strengthen these expectancy beliefs, thereby increasing likelihood of adoption.

Participants' concerns about tool complexity further illustrate the centrality of effort expectancy, while their interest in technologies that simplify decision-making reflects performance expectancy in practice. In this context, age and experience functioned as moderating factors, consistent with UTAUT2 predictions, where older users expressed more apprehension, and younger participants showed greater willingness to experiment with D3M tools.

The study also revealed that facilitating conditions and social influence are critical in shaping D3M engagement. Inadequate training opportunities, limited technical support and weak institutional communication created negative facilitating conditions, eroding confidence. Simultaneously, prevailing peer norms and departmental cultures reinforced low social influence, where data use was neither expected nor rewarded. Such sentiments demonstrate how entrenched cultural practices and social cues discourage experimentation, sustaining traditional, intuition-based decision-making. Addressing these cultural and structural constraints thus requires deliberate change management and leadership modelling to establish D3M as both a legitimate and expected practice within institutional life.

The findings also align with self-efficacy theory, which posits that individuals' beliefs in their capability to perform specific tasks influence both their motivation and persistence (Bandura 1997). Participants with higher self-efficacy, those confident in their ability to interpret and act upon data, were far more likely to engage in D3M, echoing evidence from previous studies on technology adoption (Nguyen et al. 2020; Schildkamp et al. 2017). Conversely, individuals with low self-efficacy exhibited avoidance behaviours, anxiety and resistance, even when resources were available.

Taken together, these relationships affirm that behavioural intention toward D3M adoption is not a purely technical construct but a socio-psychological one. Effective adoption depends on both cognitive readiness, developing the necessary knowledge and understanding, and emotional readiness, fostering confidence, trust, and a sense of belonging within a data-informed culture. Institutions must therefore address these dual dimensions simultaneously by providing accessible tools, contextualised training and psychologically safe environments where learning through experimentation is supported rather than penalised.

## Strategic implications for higher education institutions

The findings have several strategic implications for HEIs seeking to adopt and integrate D3M practices into their processes.

### Awareness and communication strategies

The study recommends implementing awareness campaigns to help stakeholders understand the benefits and applications of D3M. These campaigns should use practical examples and success stories relevant to participants' work contexts. Furthermore, it is important that these campaigns be conducted before the training programmes or implementation of D3M practices.

### Comprehensive training programmes

Institutions should develop multi-tiered training programmes that address the stakeholders' different skill levels and learning preferences. This study recommends that training programmes should include both technical skills development and confidence-building components. It may be worthwhile to consider gamifying some of the training programmes to enhance engagement.

### Supportive implementation approaches

Findings reveal that it is intimidating to implement major changes at once, particularly for stakeholders with low self-efficacy. As such, the study recommends gradual

implementation strategies that allow for incremental learning and success, as they help build confidence and reduce anxiety. This can be achieved through pilot projects and peer support systems, facilitating smoother transitions.

#### Age-sensitive approaches

The findings revealed that age is a moderating factor in D3M adoption. Therefore, recognition of age-related differences in technology adoption requires customised approaches that respect different learning styles and career stage considerations.

## Recommendations

Based on the study findings, the study proposes recommendations for HEIs that want to enhance D3M adoption. These proposed recommendations are categorised based on the time horizon to ensure effective adoption, implementation and continuous integration of D3M approaches.

### Immediate actions

#### Conduct awareness campaigns

The institution should educate stakeholders about the benefits and applications of D3M relevant to their specific work context through systematic awareness programmes, as findings reveal a lack of awareness among participants. Kokkinou et al. (2024) propose that sharing practical examples of the benefits and successes of technology is necessary for cognitive acceptance among stakeholders. In HEIs, short webinars on how D3M improved student throughput or resource allocation in other institutions replicate this effect. However, the campaigns must be discipline-specific to avoid overwhelming the stakeholders, as recommended by Earl and Katz (2002).

#### Assess current capabilities

Results show that stakeholders are motivated by training sessions that address their needs. As such, institutions should conduct comprehensive skills assessments to identify specific training needs across different stakeholder groups. Training programmes should be customised to address the stakeholders' skills needs. Empirical evidence shows that generic training fails where prior skill distributions are not uniform (Marelda & Wikaningrum 2022; Opoku, Pobee & Okyireh 2020). A diagnostic assessment is therefore necessary to benchmark skills in various aspects of D3M, providing the information needed to customise subsequent interventions, thereby avoiding the one-size-fits-all pitfall repeatedly observed in South African public universities (Cele 2021; Selowa et al. 2022).

#### Develop targeted training

Skills assessment is done to advise on designing training programmes. The study proposes that the institution should follow up skills assessment with the creation of multi-level training programmes that address different skill levels, with particular attention to confidence-building and practical application. However, workshops and training programmes that do not address day-to-day tasks do not enhance technology use. As such, institutions of higher learning should develop practical training programmes with direct relevance to the target groups' daily activities. Furthermore, following the skills diagnostic assessment, the training programmes developed should be at the appropriate skills level, focusing on confidence-building and maintaining D3M use.

### Medium-term strategies

#### Establish data-driven decision-making champions

The study proposes that the institution identify and train individuals who can serve as peer mentors and advocates within their departments. Research shows that resistance to change among technology adopters declines once there is evidence of success. As such, the institutions should create and formalise a D3M champions programme, where departments or individuals are appointed to lead and mentor peers on D3M use, as suggested by Arco-Tirado, Fernández-Martín and Hervás-Torres (2019), who reported improvement in performance through peer-mentoring.

#### Create pilot projects

Findings reveal that stakeholders are willing to use D3M, provided it does not require too much time and effort. To address this and to minimise technology anxiety, the study recommends using pilot projects with small increments. This also reduces the risk by creating 'safe to fail' spaces.

#### Build support systems

Continuous support is necessary for the successful adoption of technology. The study proposes institutionalising technical and emotional support through help desks, peer networks and refresher workshops to prevent regression to traditional practices.

### Long-term initiatives

#### Cultural change management

The study recommends that HEIs adopt sustained and intentional change management strategies to address cultural resistance and normalise D3M as part of the institutional ethos. Literature underscores that organisational culture evolves through repeated and reinforced practices; thus, the consistent application of D3M across all core functions, such as strategic planning, learning and teaching, and resource allocation. Embedding D3M within policy frameworks, operational guidelines and performance management systems ensures that evidence-based practice becomes a normative expectation rather than an optional exercise. Furthermore, institutions should actively share and celebrate D3M successes, recognising and rewarding teams or individuals who exemplify evidence-informed approaches.

Over time, these practices can collectively shift the institutional culture toward one that values reflection, accountability and continuous improvement through data.

#### Continuous learning culture

Successful D3M adoption requires constant and continuous learning to keep up with technological advances. The institution should create a culture that encourages experimentation, learning from mistakes, and continuous improvement in data use. This enhances skills, improves self-efficacy and builds confidence to effectively use D3M approaches and to remain relevant and competent.

#### Integration with strategic planning

The study proposes that D3M capabilities be embedded into institutional strategic planning and performance management systems, including analytics dashboards, key performance indicators and resource-allocation algorithms. Structural integration excludes the possibility of D3M continuing to be a peripheral project and makes it a central institutional capacity.

### Limitations of the study

The findings of this study provide practical, relevant insights into the state of D3M use in South African HEIs. However, several limitations impact their reach. As a single-case study, it provides rich, in-depth insights, but limits conclusions to one institution, making transferability questionable, particularly to other institutions with different governance, resource profiles or data maturity. Further to being a single case study, the study draws conclusions from self-reported data. Reliance on self-reported interview data risks social-desirability bias, possibly understating scepticism or overstating enthusiasm for D3M.

## Conclusion

This study examined the individual and institutional factors influencing the adoption of D3M within a South African HEI. Through a qualitative, interpretivist lens, it explained how awareness, digital literacy, self-efficacy, and institutional culture collectively shape staff engagement with data practices. The findings reveal that the barriers to D3M adoption are less technological than human, rooted in perceptions, confidence and cultural norms that mediate how staff interact with data.

By applying the UTAUT2 framework alongside self-efficacy theory, the study demonstrated that behavioural intention toward D3M use is determined not only by perceived usefulness and effort but also by confidence, peer influence and organisational support. The integration of these frameworks provides a more holistic understanding of D3M adoption as a socio-technical process, one that requires both cognitive readiness (knowledge and skills) and emotional readiness (confidence, trust and psychological safety).

The study contributes theoretically by extending UTAUT2 to the higher education context of the global south, showing how individual beliefs interact with institutional culture to enable or constrain digital transformation. Practically, it highlights the importance of systematic awareness, contextualised training, mentorship and recognition mechanisms to build a sustainable data culture.

For South African universities navigating the imperatives of accountability and transformation, D3M represents an opportunity to advance equity, transparency and innovation, but only if human capability keeps pace with technological capacity. Future initiatives should therefore focus not only on data systems but also on cultivating the skills, confidence and shared purpose that allow data to inform action meaningfully.

Ultimately, this research underscores that the journey toward a data-informed university is not simply about adopting new tools; it is about shaping a new culture of evidence, reflection and empowerment.

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During the preparation of this work, the authors used Grammarly QuillBot, Paperpal for grammar and clarity and feedback on the structure of the manuscript and Mendeley for citation management. The content was reviewed and edited by the authors, who take full responsibility for its accuracy.

## Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

## CRediT authorship contribution

Silence Chomunorwa: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualisation, Writing – original draft. Carolien L. van den Berg: Conceptualisation, Supervision, Validation, Writing – review and editing. All authors reviewed the article, contributed to the discussion of results, approved the final version for submission and publication, and take responsibility for the integrity of its findings.

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## Data availability

The data supporting the findings of this study are available upon request from the corresponding author, Carolien van den Berg. The data are not publicly available because they contain information that could compromise the privacy of research participants.

## Disclaimer

The views and opinions expressed in this article are those of the authors and are the product of professional research. They do not necessarily reflect the official policy or position of any affiliated institution, funder, agency or the publisher. The authors are responsible for the results, findings and content of this article.

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