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Research Article

Teachers' AI Adoption in Namibia: A Theory of Planned Behaviour Analysis

Loide Stefanus[1, *], Gabriel Tuhafeni Nhinda[2], Irja Naambo Shaanika[2]

[1]Department of Computer Science, Namibia University of Science and Technology, Windhoek, Namibia
[2]Department of Informatics, Namibia University of Science and Technology, Windhoek, Namibia

Abstract

Artificial Intelligence (AI) holds transformative potential for education, yet it remains excluded from Namibia's secondary school curriculum. The reasons for this exclusion are unclear. However, the COVID-19 pandemic exposed fundamental flaws in the lack of AI integration, as the education sector—like many others—faced significant disruptions. Introducing AI education and incorporating its use in secondary schools could enable Namibia to leapfrog in innovation and harness the opportunities presented by emerging technologies. This could drive both innovation and socio-economic growth. For this to occur, it is essential to understand teachers' perspectives on teaching AI. Grounded in the Theory of Planned Behaviour (TPB), this study investigates Namibian teachers' behavioural intentions to teach AI, examining the roles of attitudes, subjective norms, and perceived behavioural control, alongside implementation challenges. A mixed-methods approach was adopted, combining surveys with exploratory factor analysis (EFA) involving 22 teachers from the Khomas Region. While the primary aim—assessing TPB constructs (attitudes, subjective norms, and intentions)—was achieved, predictive analysis was limited by sample size. EFA extracted three TPB-aligned factors: attitude (ATT), behavioural intention (BI), and subjective norm (SN). However, statistical power was insufficient for regression or structural equation modelling (KMO = 0.50; Bartlett's $p < 0.001$), reflecting the need for broader sampling. Demographically, most participants (54.5% male, 45.5% female) were aged 30–39, held honours degrees, and taught in urban public schools. Despite low perceived behavioural control (e.g., limited resources), teachers reported strong intentions to teach AI, driven by positive attitudes and social expectations. The findings highlight the TPB's relevance in Namibia's AI education context while revealing systemic barriers. To facilitate adoption, policymakers must address resource gaps, provide teacher training, and improve infrastructure. This study offers a foundational TPB-based framework for future research in under-resourced educational settings.

Keywords

Artificial Intelligence in Education, Theory of Planned Behaviour, Teacher Technology Adoption, Namibian Education, Secondary Education

1. Introduction

Technological advancements have fundamentally transformed modern society, culminating in the emergence of artificial intelligence (AI) as a product of innovations in computing, automation, and information technologies [1]. As

*Corresponding author: loidemweneni@gmail.com (Loide Stefanus)

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the world transitions toward the Fourth Industrial Revolution (digital transformation), these changes profoundly impact lifestyles and education systems. In this context, digital literacy, particularly AI proficiency, has become essential for adapting to evolving societal demands.

Chen *et al.* identified AI as a catalyst for innovation across all sectors, including education [1]. However, the Namibian education system faces significant challenges, including limited personalised learning opportunities and a critical shortage of AI-related competencies among educators. The integration of AI as a compulsory subject could address these gaps while generating broader societal benefits across key sectors such as agriculture and healthcare. Secondary-level AI education promises to develop learners' critical thinking and problem-solving skills through authentic, technology-driven applications [2].

AI serves as a catalyst for innovation across sectors, including education [3]. AI's capacity to simulate human cognition has driven its adoption in global education systems [3], yet its introduction at K-12 levels presents unique implementation challenges. Teachers' behavioural intentions - shaped by attitudes, subjective norms, and perceived behavioural control according to TPB - represent a crucial determinant of successful AI integration [4]. While international research has examined AI in education, few studies have investigated teacher readiness in sub-Saharan Africa, and none have specifically applied the TPB framework to Namibian educators' willingness to teach AI [5].

Existing studies predominantly focus on learners' intentions to engage with AI [6-8], with limited investigation into teachers' perspectives, especially in developing nations [3]. In Africa, AI research is notably underrepresented, creating a critical gap in context-specific policy and implementation strategies [4, 9]. This study addresses this gap by examining Namibian secondary school teachers' behavioural intentions towards teaching AI, while identifying perceived challenges in curriculum integration.

This study seeks to address these research gaps through three primary objectives: (1) to examine Namibian secondary school teachers' behavioural intentions towards teaching AI through the theoretical lens of TPB; (2) to identify and analyse the key challenges impeding effective AI integration within the Namibian educational context; and (3) to develop evidence-based policy recommendations for successful AI implementation in resource-constrained environments. By focusing on educators' perspectives, this research provides critical insights for curriculum development and teacher training programmes in Namibia and comparable educational systems.

The paper is organised as follows: the first section covers the introduction of the study and, research objective. Section 2 presents a comprehensive review of relevant literature, encompassing both theoretical foundations and empirical studies of AI in education. Section 3 details the research methodology, including the study design, data collection procedures, and analytical techniques. The subsequent section presents the research findings, followed by a discussion that interprets these results within the TPB framework and broader educational context. The final section offers substantive conclusions and policy recommendations, while acknowledging study limitations and suggesting directions for future research.

2. Literature Review

2.1. Artificial Intelligence in Education

Artificial Intelligence (AI) has been widely recognised as a transformative tool for enhancing education quality, enabling personalised learning [10], and preparing students for the evolving workforce demands [1]. Contemporary AI platforms adapt dynamically to learners' individual requirements and knowledge levels, creating more efficient and streamlined educational processes [11]. These technological advancements have significantly facilitated both teaching and learning experiences. Chen *et al.* conducted a systematic literature which examined numerous studies on AI applications in education, demonstrating measurable improvements across multiple domains [1]. Specifically, AI has been successfully utilised for automating administrative procedures, developing curriculum content, enhancing instructional methods, and improving student learning outcomes [1]. Particularly noteworthy are web-based AI solutions that have revolutionised administrative tasks such as student assessment, automated grading systems, and personalised assignment feedback [3].

Beyond its role as an educational tool, AI represents a critical subject matter that should be incorporated into school curricula. The broader applications of AI across sectors underscore its pedagogical value - for instance, [12] documented how AI implementation has increased agricultural productivity, while [13] highlighted its transformative impact on medical practices and healthcare services. Teaching AI at the secondary level would therefore provide learners with transferable skills applicable to diverse future careers, while cultivating problem-solving capabilities for real-world challenges [1]. Furthermore, AI education offers practical benefits for teachers, reducing administrative burdens associated with paperwork and enabling greater focus on pedagogical facilitation through technology-enhanced learning environments.

2.2. Theories for Determining Intentions

Various theories determine the intentions of humans to perform a certain action, which include the theory of acceptance model (TAM), the theory of reasoned action (TRA), and the theory of planned behaviour (TPB) [14]. Developed by Fishbein and Ajzen (1975), TRA posits that behavioural intentions arise from two key factors: personal attitudes (individual interest in the behaviour) and subjective norms (perceived social pressures) [15]. This framework establishes that actual behaviour manifests through intentionality, which itself derives from these cognitive and social influences.

The Technology Acceptance Model (TAM) specifically addresses technological adoption, proposing that perceived usefulness (expected functional benefits) and perceived ease of use (technical accessibility) primarily govern an individual's willingness to adopt new systems [16]. While TAM offers valuable insights into technology-specific decision-making, the Theory of Planned Behaviour (TPB) provides a more comprehensive model by incorporating an additional critical dimension: perceived behavioural control (self-efficacy and resource availability) alongside attitudes and subjective norms [17]. This tripartite structure makes TPB particularly suited for examining complex behavioural adoption in educational contexts, where institutional constraints and personal capabilities significantly influence outcomes.

Given its robust explanatory power for volitional behaviours in resource-constrained settings, this study employs TPB as its central theoretical framework to analyse Namibian educators' intentions to adopt AI in secondary classrooms. The subsequent section elaborates on TPB's applicability to educational technology integration, with particular attention to perceived control barriers in low-resource environments.

2.3. Theory of Planned Behaviour

This study is grounded in the Theory of Planned Behaviour (TPB). TPB was developed by Ajzen (1985), and it is a widely used theoretical framework for researching human behaviour in various fields [18]. Since its development, several research models such as the three renowned technology acceptance models (TAM) were developed based on the TPB [19].

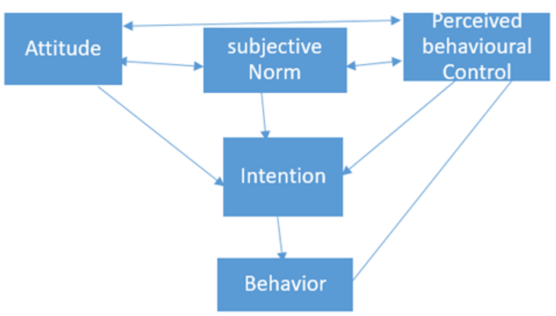

Figure 1. *Theory of planned behaviour.*

The Theory of Planned Behaviour components are discussed as follows:

2.3.1. Behaviour Intention

Behavioural intention pertains to an individual's plan or decision to partake in a specific behaviour or action in the future. According to TPB, behavioural intention stands as the most crucial determinant of behaviour [20]. The intention to engage in a behaviour is influenced by factors such as attitudes, subjective norms, and perceived behavioural control [18]. Kao *et al.* revealed that demographic variables, such as gender and age, indirectly affected teachers' behavioural intentions regarding web-based professional development [21]. Age exerted a negative influence on perceived behavioural control, subsequently impacting these behavioural intentions adversely [21].

2.3.2. Attitude

Attitude refers to an individual's positive or negative feelings or behaviour towards an idea. Attitudes can be influenced by various factors such as values, beliefs, emotions, and experience. Kao *et al.* study attitude and perceived behavioural control were the primary contributing factors that influenced the behavioural intentions of elementary school teachers towards teaching AI [21].

2.3.3. Subject Norm

The subjective norm is defined as individuals' normative beliefs concerning how others perceive or judge engagement in a specific behaviour [22]. Subjective norms involve an individual's perception of what others think about a behaviour, especially those who intend to carry out the behaviour, and it may not necessarily reflect the actual opinions of others.

2.3.4. Perceived Behavioural Control

Perceived behavioural control refers to an individual's perception or interpretation of another person's behaviour. Mohr and Kühl postulate that perceived behavioural control is believed to exert a greater influence on intentions to accept a behaviour, followed by attitude towards AI [12]. TPB combines an individual's personal attitude and opinion with their perceived control over the behaviour, as well as society's subjective norms, to influence their behavioural intentions. These intentions, in turn, drive their actual behaviour or actions. In the context of teachers' intentions to integrate AI into schools, they will assess their intention to do so [23].

2.4. Challenges Associated with Teaching Artificial Intelligence

During 2020, when there was a SARS CoV-2 pandemic, there was an interruption in schooling and academic spheres [23]. Globally, the pandemic had a negative impact on education, leading to high dropout and increased failure rates [23]. As a response to school closure, the Namibian Ministry of Education, Arts and Culture proposed that schools make use of eLearning as a strategy to ensure learning continues remotely. Unfortunately, this was not possible due to challenges such as a lack of computers, internet, and limited digital literacy skills facing schools, learners, and teachers [24].

Teaching AI in schools also raises ethical and social implications that need to be addressed. Baidoo-Anu and Owusu Ansah argue that ChatGPT is one of the AI generative tools which promote personalised and interactive learning, generating prompts for formative assessment activities that provide ongoing feedback to inform teaching and learning [25]. This tool has limitations such as generating wrong information, biases in data training, which may augment existing biases, and privacy issues [26].

According to a study by UNESCO (2019), lack of access to AI tools and resources is a significant barrier to the expansion of AI education in schools. The study further notes that schools need to find innovative ways to overcome this barrier, such as partnering with technology companies or using open-source AI tools. Lack of infrastructure is another concern with teaching artificial intelligence in schools, given that some schools were built decades ago and the infrastructure cannot accommodate technological tools such as smartboards. Some of the schools' infrastructures do not have electricity, making it difficult for the usage of AI tools.

Teaching AI in schools requires a multidisciplinary approach that includes computer science, ethics, and social sciences [26]. Teachers need to address the ethical and social implications of AI in their teaching to prepare students for the future of AI [27].

3. Methodology

This section discusses the methods used in this study to collect and analyse data.

3.1. Research Method, Instrument and Population

This study employed a sequential mixed-methods design to examine Namibian secondary teachers' intentions to teach artificial intelligence (AI), operationalised through the Theory of Planned Behaviour (TPB) framework. Data were collected via an online survey administered to 22 teachers in the Khomas Region, selected purposively for their access to technological infrastructure. The survey comprised six sections assessing demographics, behavioural intentions (BI), attitudes (ATT), subjective norms (SN), teaching intentions, and implementation challenges, with Likert-scale and open-ended questions enabling quantitative and qualitative analysis. Ethical approval was obtained from the Faculty Research Ethics Committee at the Namibian University of Science and Technology (FREC-registration number: FREC – 43/23), with participants providing informed consent electronically.

3.2. Data Analysis

Quantitative data were analysed using Jamovi software, where exploratory factor analysis (EFA) with principal axis extraction and oblimin rotation was conducted to validate the TPB factor structure, supplemented by descriptive statistics. Given the small sample size (n=22), the study prioritised descriptive and exploratory analyses over inferential statistics, as recommended for samples below 50 [28]. Thematic analysis of qualitative responses contextualised quantitative findings [29], particularly regarding implementation barriers.

To enhance reproducibility, the full survey instrument and EFA outputs (including scree plots and factor loadings) are provided in Supplementary Materials S1-S2. While the Kaiser-Meyer-Olkin measure (KMO=0.50) indicated marginal sampling adequacy, Bartlett's test of sphericity ($p<0.001$) confirmed the data's suitability for preliminary factor analysis [Shrestha, 2021], yielding the theoretically aligned three-factor solution (ATT, BI, SN) reported in the Results.

4. Results

The results of this study are discussed in this section. Quantitative and qualitative data were analysed. The results are presented as follows:

4.1. Participants' Demography

The study recruited 22 secondary school teachers from Namibia's Khomas Region through purposive sampling. Participant demography is focused on gender, age, qualification, school type, and school location. As illustrated in Figure 2, the cohort comprised slightly more male educators (54.5%, n=12) than female (45.5%, n=10). As detailed in Table 1, the majority taught in public schools (95.5%, n=21), predominantly located in urban areas (59.1%, n=13). Participants were predominantly aged 30-39 years (36.4%, n=8), with no respondents over 60. Academic qualifications showed a strong skew toward honours degrees (45.5%, n=10), followed by bachelor's degrees (27.3%, n=6) and master's degrees (22.7%, n=5).

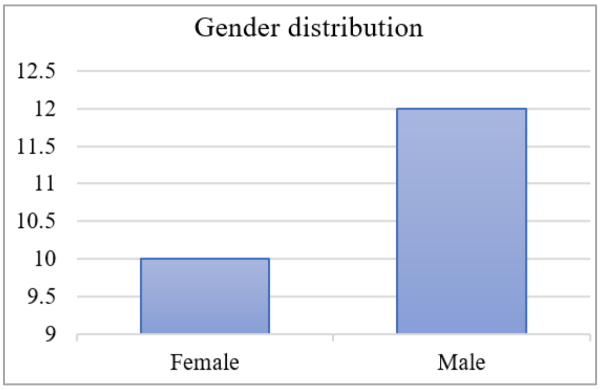

Figure 2. Gender distribution.

Table 1. Demographic result (N=22).

Participant demographics			
Items		Frequency	Percentage
Gender	Female	10	45.5%
	Male	12	54.5%
	Others		
Age (years)	20-29	6	27.3%
	30-39	8	36.4%
	40-49	5	22.7%
	50-59	3	13.6%
	60 and above	00	
School type	Private	01	4.5%
	Public	21	95.5%
School location	Urban	13	59.1%
	Rural	09	40.9%
Qualification	PhD	00	
	Master	05	22.7%
	Honour	10	45.5%
	Degree	06	27.3%
	Diploma	01	4.5%
	Grade 12	00	

4.2. Exploratory Factor Analysis

The first aim of this study was to explore the behavioural intentions, attitudes, and subjective norms Namibian teachers have towards teaching AI in schools. The second aim assess how teachers' attitudes and subjective norms predict their intentions to teach AI in schools. While the first aim was fully achieved, the second aim was not fully realised due to sample inadequacy in measurement. After accomplishing the first objective, an exploratory factor analysis (EFA) was conducted to determine the number of factors influencing variables and to analyse which variables could form a factor or construct. Table 1 displays the EFA output. While Bartlett's Test of sphericity for the EFA-extracted factors was significant ($p < .001$), the Kaiser-Meyer-Olkin (KMO) measurement of sample adequacy was 0.50, falling below the recommended value of 0.80 [30]. A KMO value between 0.50 and 0.60 is considered suboptimal (Schreiber, 2021). Additionally, the chi-square (χ^2) value was undefined (inf), likely due to the very small sample size (22) in this study. Based on these limitations, in-depth analyses are hindered. While the chi-square statistic is influenced by the sample size, experts advise against using chi-square when the sample size is below 50 [28]. This indicates that the sample size in this study is too small for inferential statistics such as correlation, confirmatory factor analysis, regression analysis, or structural equation modelling. Using the Principal Axis Extraction method with 'oblimin' rotation, three factors—attitude (ATT), behavioural intentions (BI), and subjective norm (SN)—were extracted. I retained these three factors with a fixed number (3) of factors, and no items were added or deleted from any of the three factors.

Table 2. Factor Loadings of the Exploratory Factor Analysis Output.

	Factor			
	1(ATT)	2(BI)	3(SN)	Uniqueness
IncludeAIinTeachingCirrulum (ATT_1)	1.020			0.0155
SeekAdditionalSupport (ATT_2)	0.997			0.0386
EncourageTeachToIntegrateAI (ATT_3)	0.978			0.0206
IncludeAI (ATT_4)	0.889			0.1464
ComfortableWithAI (ATT_5)	0.851			0.1657
IntergrateAI (ATT_6)	0.822			0.3160
AllocateTimeToteachAI (ATT_7)	0.788			0.2644
SeekAdditionalResource (ATT_8)	0.660			0.2632
AIImportantForFuture (ATT_9)	0.561			0.2714
ConfidentToTeachAI (ATT_10)	0.541			0.5992
EncourageEngagementOfAI (BI_1)		0.979		0.0324

	Factor			
	1(ATT)	2(BI)	3(SN)	Uniqueness
WillingnessToAttendWorkshop (BI_2)		0.979		0.0324
AIBenefitOtherSectors (BI_3)		0.979		0.0324
interestedToTeachAI (BI_4)		0.552		0.5301
AIValuable (BI_5)		0.491		0.3947
OpenToReceiveTrainingOnAI (SN_1)			0.897	0.1263
EncourageStudent (SN_2)			0.897	0.1263
FeelSocietalPressure (SN_3)			0.615	0.5490
PositivelyInfluencedByColleaques (SN_4)			0.389	0.7931
PercieveSupportFromSuperior (SN_5)			0.336	0.7474

Note. 'Minimum residual' extraction method was used in combination with a 'oblimin' rotation

Bartlett's Test of Sphericity		
χ^2	df	P
Inf	190	< .001

The internal consistency of the three TPB factors was confirmed through both Cronbach's alpha (α) and McDonald's omega (ω) coefficients, as presented in Table 3. All constructs demonstrated strong reliability, with attitude (α =.951, ω =.965), behavioural intention (α =.827, ω =.935), and subjective norms (α =.795, ω =.827) exceeding the recommended threshold of 0.70 [31]. These results establish the measurement instruments' robustness for descriptive analysis, with several notable observations: (1) the attitude scale showed particularly high reliability (α>.90), suggesting exceptional item homogeneity; (2) while subjective norms had slightly lower reliability, its ω value still indicated adequate composite reliability for group-level analysis; and (3) the close alignment between α and ω values for each factor confirms minimal tau-equivalence violation. These psychometric properties fully address the study's first research question regarding the validity of TPB constructs in measuring teachers' AI adoption intentions, though the modest reliability for subjective norms warrants caution when interpreting individual item responses within this factor.

Table 3. Scale Reliability statistics.

	Mean	SD	Cronbach's alpha (α)	McDonald's (ω)
Factor 1(ATT)	3.88	0.697	0.951	0.965
Factor 2(BI)	3.64	0.342	0.827	0.935
Factor 3(SN)	2.56	0.464	0.795	0.827

4.3. Teachers' Intention to Teach AI

This section is about the teacher's intention to teach AI in schools. The categorical responses (i.e. 3=Yes, 2=No, 1=Not, sure) were provided to respondents to choose from to answer 7 sections. As shown in the table below, the teachers have the intention to teach as shown in Table 2 (M= 2.601).

***Table 4.** Teachers' intention in teach.*

	Response			**mean**	**SD**	**No**
	3= yes	**2= no**	**1= not sure**			
Do you intend to include artificial intelligence as a subject in your teaching curriculum?	17	4	1	2.73	0.550	22
Do you think it is necessary to integrate Artificial intelligence in classroom?	20	1	1	0.86	0.468	22
Are you planning to seek additional resources or materials	20	2		2.91	0.294	22
Are you willing to attend workshops or conferences related to teaching artificial intelligence?	21 2		1	2.95	0.213	22
Are you open to receiving training or professional development opportunities to enhance your knowledge and skills in teaching artificial intelligence?	20	1	1	2.86	0.468	22
Will you encourage students to explore and engage with artificial intelligence	21 2	1		2.95	0.213	22
Do you believe that teaching artificial intelligence in school will be benefit other workforce, apart from education in future?	21	1		2.95	0.213	22
Total				2.60		

4.4. Teacher's Attitude

This part of the survey section presents teachers attitude towards teaching AI in secondary school. The Five Likert-type scale (i.e., 1=strongly disagree, 2=Disagree, 3=Neutral, 4=Agree and 5=Strongly Agree) to rate teachers' attitude towards teaching AI and provided with 3 items. Most of the respondent have positive attitude towards teaching as indicated in Table 3 (*M*=4.60).

***Table 5.** Teacher's Attitude towards AI.*

Items	**Choices**					**Mean**	**SD**
	5= strongly Agree	**4= agree**	**3= neutral**	**2= disagree**	**1=Strongly disagree**		
I am interested to integrate Artificial intelligence into my teaching methods	16	4	2			4.64	0.658
I am feeling confident in my ability to teach artificial intelligence effectively	12	9	1			4.50	0.598
I believe that teaching artificial intelligence is valuable for students' education	17	3	2			4.68	0.646
Total						4.60	

4.5. Subjective Norm

In this section of the survey, respondents were provided with responses to choose from (3= Yes, 2=No and 1 = not sure) to answer 3 items. The mean of 2.36 indicate that average number of respondents are somewhat positively influenced by their colleagues when making decision to teach or use AI. The result show that respondents perceive support from the superiors and school administrators. The result also shows that respondent feel societal pressure to include artificial intelligence in their teaching.

Table 6. Subjective norm.

Subjective Norm						
Items	Choices			Mean	STD	No
	3=Yes	2=No	1= Not sure			
Do your colleagues positively influence your decision to use/teach artificial intelligence?	10	6	6	2.18	0.853	22
Do you perceive support from your school administration or superiors in teaching artificial intelligence?	12	9	1	2.50	0.598	22
Do you feel societal expectations or pressures to include artificial intelligence in my teaching?	11	9	2	2.41	0.66	22
Total				2.36		

4.6. Challenges Facing the Integration of AI

Education in Namibia is faced with challenges that hinder the integration of an AI curriculum. These challenges are broadly defined as difficulties or obstacles that hinder the effective and equitable delivery of quality education. These challenges include a lack of computers, internet access, and substandard infrastructure. The absence of these essential components exacerbates the difficulties faced in incorporating AI into the curriculum. The participants were presented with open structured questions about the challenges, barriers and resources that hinder the integration of AI. The respondent highlighted the inadequate technological resources in schools, limited/ few computers, absence of internet in schools, more even the infrastructure standard. One participant responded as follows "Reliable Internet connectivity". Teachers have also indicated that learners' attitude/ understanding, and difficulty of AI concept are some of the obstacles that hinder teachers from integrating AI into their teaching methods. According to [29], there is a widespread sentiment that the existing education system is failing to produce an adequate number of specialists, and regular users are finding it progressively challenging to comprehend the systems they encounter. Moreover, Namibia is producing enough teachers, only that they are not trained in AI aspects. More teachers indicated that a lack of skills and training on AI was a barrier to incorporating AI into their teaching, with a few perceiving that learners' understanding and interest.

4.7. Perceived Challenges in Incorporating AI into Teaching

Most of the participants indicated a lack of resources, such as computers, internet, as a challenge. Another challenge is that some schools lack proper infrastructure and facilities. Other participants indicated that learners find the AI concept difficult. Teachers perceive a lack of skills in AI concepts among themselves, teachers are not trained on how to use AI tools in their teaching method. One of the respondents indicated that "Lack of skills to use artificial intelligence" is one of the challenges.

4.8. Discussion and Conclusion

This study examined Namibian secondary teachers' intentions to teach AI through the Theory of Planned Behaviour (TPB), yielding three key insights that extend current literature while addressing gaps in African educational contexts. Teachers demonstrated strong intentions to teach AI (M=2.60), particularly in workshop attendance (95.5%) and curriculum integration (77.3%). These results align with Chai *et al.*'s findings in Chinese schools, where positive attitudes significantly predicted AI adoption intentions [6]. However, our higher intention scores compared to Jatileni *et al.*'s Namibian study (45% willingness) suggest regional disparities within Namibia, possibly due to our Khomas Region focus, where technology access is superior [14]. The exceptional attitude scores (M=4.60) mirror [16]'s chatbot acceptance research, confirming that perceived pedagogical value outweighs implementation barriers when technologies are viewed as educationally transformative.

While 90.9% recognised AI's necessity, qualitative data revealed persistent resource concerns—echoing [23]'s identification of Namibia's "educational emergency" in technology adoption. This infrastructure paradox aligns with [12]'s agricultural AI research, where intention-behaviour gaps persisted despite positive attitudes in resource-constrained environments. Our urban-skewed sample (59.1%) may have inflated perceived feasibility compared to [24]'s Indonesian digital literacy challenges, suggesting rural implementations may face steeper adoption curves.

Administrative support (54.5%) emerged as the strongest normative predictor, contrasting with [7]'s peer-dominated findings in Asian contexts. This implies institutional leadership is pivotal in Namibia's centralised education system—a nuance absent in [22]'s hospitality studies. Overall, our factor analysis validated TPB's structure, but the low KMO (0.50) supports [18]'s argument for contextual TPB modifications in Global South education. While attitudes were stellar, implementation concerns persist—a phenomenon [29] attributed to "responsible AI" literacy gaps in teacher training.

As policy recommendations, echoing the Ministry of Education's decentralised approach to education to training in AI with AI-champions would provide greater training opportunities. Integrating AI in teacher education could lead to responsible AI as denoted by [29]. Not only integration of AI, but also AI pedagogy.

In conclusion, this study sheds light on the status of AI education in Namibian secondary schools, specifically focusing on teachers' behavioural intentions. It further provides the first TPB-based analysis of AI teaching intentions in Namibian secondary schools, confirming that while attitudes are positive (M=4.60), realisation requires systemic support from varying education stakeholders. Ayanwale *et al.* emphasise that it is crucial to know teachers' readiness to teach AI in school [3]. The result of this study shows that teachers need support from various stakeholders to successfully integrate and implement AI in schools. Teachers should be trained on AI platforms to gain skills. Furthermore, higher education institutions' curricula should incorporate teachers' training on AI. The respondents of this study highlighted the lack of AI skills as a challenge that hinders the usage of AI in schools. Akgun and Greenhow caution, successful implementation must balance technological adoption with ethical considerations, particularly crucial in Namibia's resource-constrained context [27]. Our findings offer policymakers evidence to design phased AI integration strategies that address both human and infrastructural readiness gaps.

5. Future Direction

Our study has several limitations which future researchers could consider as a new direction for research. Firstly, subjective norms' lower reliability (α=.0.795) warrants [28]'s thematic analysis techniques for deeper exploration. The small sample size (n=22) limits generalisability but provides a starting point for this research area with scant literature. A longitudinal study that removes the skewed representation of rural vs urban schools and one that mirrors Namibia's gender representation in teachers might yield definitive results.

Building upon the understanding gained from the current study, the focus should shift towards developing targeted interventions and strategies to enhance teachers' readiness and willingness to integrate AI into their pedagogical practices. Collaborative efforts with educational institutions, policymakers, and professional development providers can be explored to design and implement effective training programs that address the specific needs and concerns identified among Namibian educators.

Abbreviations

AI	Artificial Intelligence
TPB	Theory of Planned Behaviour
EFA	Exploratory Factor Analysis
BI	Behavioural Intentions
ATT	Attitudes
SN	Subjective Norms

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Author Contributions

Loide Stefanus: Data collection, Methodology, Analysing Data, Writing- original draft.

Gabriel Tuhafeni Nhinda: Proof-reading, Supervision, Writing- reviewing and editing.

Irja Naambo Shaanika: Proof-reading, Writing- reviewing and editing.

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Data Availability Statement

The data that were collected for this study are available from the corresponding author upon request and with permission from the National Commission on Research Science and Technology, and the Ministry of Education, Arts and Culture on Namibia.

Conflicts of Interest

The authors declare that the research was conducted without any organisation or persons that could be considered or seen as a potential conflict.

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