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AI-enabled sign language interpretation in E-learning: a structural modelling of the perspectives of African sign language interpreters

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Abstract

The development of artificial intelligence-enabled sign language interpretation (AI-enabled SLI) is changing the dynamics in the sign language interpreting space and there have been various arguments for and against the use of AI-enabled SLI, especially for academic use. Leveraging on the importance of artificial intelligence for persons who are Deaf or hard of hearing, this study brought to forward the perspectives of professional sign language interpreters from Sub-Saharan Africa about AI-enabled SLI. Framed by the technology acceptance model, a total of 412 sign language interpreters from 12 African countries participated in the study and responded to the e-questionnaire. The survey responses were analysed using structural equation modelling. The findings revealed that perceived benefits (PB), perceived risks (PR) and perceived trust (PT) had a significant positive relationship with future perspectives (FP) about AI-enabled SLI. It was also found that while PB had a negative but direct relationship with cultural influence (CI), PT was found to be positively significant with CI. This study could not establish any significant mediative influence of CI in the relationship between PB, PR, PT and FP about AI-enabled SLI among African SLIs. Therefore, CI has not been found to have any influence on FP about AI-enabled SLI among African SLIs. Based on the findings, appropriate recommendations were made.

Keywords Artificial intelligence-enabled sign language interpretation · Students who are Deaf or hard of hearing · E-learning · Sign language interpreters

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1 Introduction

Efficient two-way auditory-verbal communication remains a major challenge for students who are Deaf or hard of hearing (Adigun, 2025), both within and outside the classrooms. Individuals who are or hard of hearing are conceptualized as those persons who are culturally bound to the Deaf community. In other words, these individuals believe primarily in the use of sign language as a means of communication (Adigun et al., 2021). Sign language (SL) is a visual/gestural language which has evolved naturally among the students who are Deaf or hard of hearing for communication purposes. Sign language has all the features of any language; that is, it is a rule-governed system using fingerspelling and symbols within the signing frame[1] to represent meaning for the purpose of exchanging communication and ideas. In sign language, the symbols are specific hand movements and configurations that are modified by facial expressions to convey meaning (Adigun, 2019; Obosu et al., 2023). Apparently, while SL is widely use for communication among the persons who are Deaf or hard of hearing, the need to communicate with hearing individuals for social and/or educational reasons necessitates the need for hearing sign language interpreters. Sign language interpreters (SLIs) using signs, finger spellings, facial expressions among others approaches facilitates the establishment of effective communication and understanding among and between persons who are Deaf or hard of hearing and hearing individuals (Adigun, 2019).

SLIs are typically individuals who hear and have the skills to switch between using sign language and verbal modes to establish and/or facilitate communication between persons who are Deaf or hard of hearing and hearing individuals. It is interesting to note that within the physical classroom settings, educational SLIs have over the years been much-needed professionals providing strong support for the academic activities of students who are Deaf (Marschark et al., 2006). In fact, within the higher education space, the role of SLIs has been acknowledged as a factor that influences the influx of students who are Deaf or hard of hearing for higher education programmes (Marschark et al., 2005; Napier & Barker, 2004). However, the dynamics of sign language interpreting have changed in recent times due to rapidly evolving advancement in technologies. Some studies have shown that artificial intelligence has been infused into sign language interpretation to resolve the emerging challenges of the shortage and/or lack of physical availability of human SLIs in difficult situations, such as during the COVID-19 pandemic, among others (Adigun 2019; Adigun et al. 2022a, b; Kaviyaraj et al., 2026; Roman et al., 2023). The development, use, and future of AI-enabled sign language interpretation (AI-enabled SLI) is generating debates among human-SLIs, particularly within the Sub-Saharan Africa.

In other words, there is a growing concern about its deployment for e-learning, largely because of the dynamics and variables, such as cultural backgrounds, home

[1] The "signing frame" is a conceptual box in front of the body, from the head to the waist, that is used for signing in sign language.

languages, and national sign languages[2] that shape sign language syntax and morphologies. According to Bragg et al. (2021), there is general concern around the deployment and use of AI-enabled SLI in Deaf education, and there is yet to be concrete evidence of how human-sign language interpreters construct and perceive the future of AI-enabled SLI for e-learning purposes, based on the cultural influence (CI), perceived benefits (PB), perceived risks (PR), and perceived trust (PT) associated with AI-enabled SLI. Cultural influence (CI) is said to be a factor that has significant potential to shape an individual's or group's beliefs, behaviours, practices, and value systems. CI is a dynamic and complex construct that has been found as a constantly evolving force that shapes public trust in technology and how people perceive the associated benefits and risks of using the technology (Appiah & Agblewornu, 2025). This study leveraged on the assumptions and principles of the Technology Acceptance Model (TAM) by Davis (1986) to gain a comprehensive understanding of the effects of PB, PR, and PT on the FP of AI-enabled SLIs (See: Fig. 1) among African SLIs, even with the effect of the CI.

For more than three decades, the TAM has been used as a theoretical framework to provide a scientific explanation to intention and peoples' behaviour towards technologies based on the perceived usefulness (PU) and perceived ease of use (PE) of such technologies. Studies have shown that findings obtained based on PU and PE can be used to determine perceived peoples' (in this case, African SLIs) intention and behaviour towards technologies. In todays' knowledge economy, a major fact is that while new technology is emerging almost on daily basis, the application of such emerging technologies has been critiques based on potential benefits and risks associated with the adoption, deployment, and use of such technologies. Associated benefits and risks are critical to potential development of trust in the use of such tech-

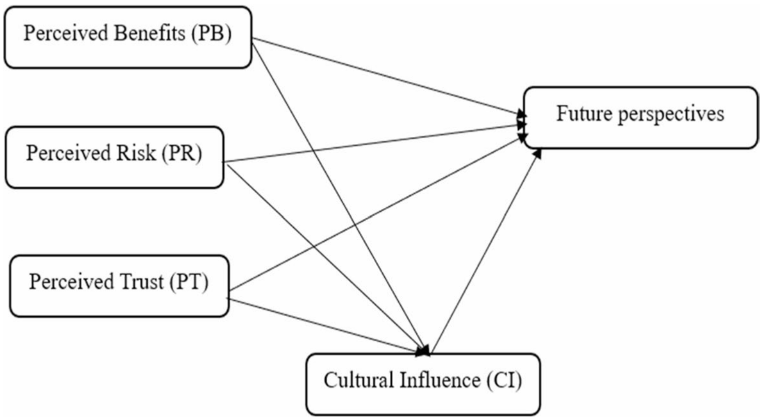

Fig. 1 Conceptual model of the study

[2] National sign languages are the natural, complete languages used by the Deaf communities of a specific country, such as the American Sign Language (ASL), Namibian Sign Language (NSL), South African Sign Language (SASL), and many others.

nologies. Interestingly, despite critical analysis of benefits, risks and perceived trust in emerging technologies, the influence of cultural dynamics can play a significant role in acceptance and use of such technologies. In other words, despite perceived usefulness (PU) and perceived ease of use (PE) of such technologies that shapes intention to use AI-enabled sign language interpretation for e-learning purposes, professional interpreters' perspectives on the future of AI-enabled SLI for e-learning may have significant implication for deployment and use of such AI-mediated sign language interpretation.

In this study, future perspective (FP) was used to signal both intention and behaviour of professional Sign Language Interpreters from selected Sub-Sahara African countries about AI-enabled sign language interpretation while PB, PR, and PT, and CI were shaped by the position of PU and PE of the TAM model. By implication, this quantitative study which examined the professional interpreters' perspectives on AI-enabled SLI for e-learning extends the Technology Acceptance Model (TAM). Although studies have shown that the role of attitude and culture towards emerging technologies cannot be overlooked (Kao & Sapp, 2022; Emon & Khan, 2025; Brauner et al., 2024), but the mediating effects of cultural influence on the PB, PR, and PT regarding future perspectives of AI-enabled SLI in Africa are yet to be ascertained in existing studies. Thus, this current study bridges the identified research gap by structurally modelling African SLIs' future perception (FP) of AI-enabled SLI through CI, PB, PR, and PT. It is believed that the outcome of this study will contribute significantly to academic discourses on issues that concerns professional interpreters' perspectives on AI-enabled SLI for e-learning. Findings obtained in the study will positively re-orientate the perceptions of African SLIs and clarify the implications of cultural interference in the use of AI-enabled SLI for students who are Deaf or hard of hearing. Lastly, the findings of this study will critically shape policy issues and pedagogical practice that advance the adoption of AI for equitable learning opportunities in virtual learning environments across the African continent.

2 Literature review

2.1 Evolution of technology and artificial intelligence in sign language interpretation

Uninterrupted access to information by persons who are Deaf or hard or hearing has been a longtime issue partly because effective sign language communication requires direct two-way interaction with a sign language interpreter. While studies indicated that the need for physical and direct interaction with a sign language interpreter may be time consuming, the need of technology-enhanced sign language interpretation is inevitable (Adigun & Nzima, 2021; Ngubane & Adigun, 2024; Vidhyasagar et al., 2023). Thus, in the last three decades, there has been a significant shift in the development of technology induced sign language translation for the sole purpose of facilitation of enhance communication and advancement of social inclusion of persons who are Deaf or hard of hearing. Although, despite various research efforts, technologically enhanced sign languages are still confronted with several challenges and there is currently lack of consensus on universal technologically enhanced sign language for use by persons who are Deaf or hard or hearing (Papastratis et al., 2021). The presence of numerous and culturally diverse sign languages, standardization of large sign language datasets and lack of large-annotated datasets among others have significantly influences automation of sign languages. Although, recent advancement in technologies through machine learning and several models of artificial intelligence mechanism is currently gaining attention and it has shown some promising development (See: Najib, 2025; Strobel et al., 2023) but viability and potency of AI-enabled sign language translation is currently generating heated debated among relevant stakeholders included among persons who are Deaf or hard of hearing.

2.2 AI-enabled sign language interpreting (AI-enabled SLI): Perspectives and concerns

Advancements in artificial intelligence (AI) continue to revolutionise not only education but also communication models. Among the community of persons who are Deaf or hard of hearing, AI has been found to challenge the status quo of human SLIs, and the emergence of AI-enabled SLI is rapidly evolving (CH & Fawziya, 2024). The recent advancements in sign language avatars continue to generate concerns (Adigun et al., 2025; Bragg, 2021). Overtly, besides the issue of ethical concerns, how the AI-enabled SLI performs in accurately recognising and interpreting sign language gestures, facial expressions, and emotional nuances in real-time to SL users of diverse backgrounds has been central to intellectual discourses in recent times. While AI-enabled SLI has foster inclusivity and has led to cost saving and resolved the need for the physical presence of human SLIs, the signing accuracy, quality, and acceptance due to cultural diversity among the community of persons who are Deaf or hard of hearing are still concerns. According to Bragg et al. (2019) and Tran et al. (2023), the ability of automated SL translation to differentiate precisely between two closely similar facial expressions, finger arrangements, gestures, or hand orientations is yet to be established, even among American Sign Language users.

Yin et al. (2021a, b) posit that under a controlled laboratory environment, AI-based SL translation systems have a high potential to demonstrate high accuracy, but it is very likely that in real-world scenarios, the performance of such technology may be degraded due to factors such as optimal lighting conditions, individual signing styles, cultural influences, and the personal styles of the users of such technologies, among others. A study by Kipp et al. (2011) revealed the lack of emotional sensitivity and expression in automated SL translation. Kipp et al. also noted that the missing *humanness* of a sign avatar lowers its usage and acceptance by persons who are Deaf or hard of hearing. Wolfe et al. (2022) recently noted that the technological evolution that has influenced the automation of SL is not favourably viewed and accepted within the signing communities. The lack of acceptance is due in part to the diversity in SLs across cultures and nations, as well as the poor quality of the signed language (Kahlon & Singh, 2023; Tran et al., 2023).

There are rising numbers of cases of scepticism towards automated SL interpretation. For instance, Tran et al. (2023) study showed that the ASL users were very concerned about the implications of cultural appropriation on the development of

AI-enabled SL and that the communities of persons who are Deaf or hard of hearing values and needs could be overlooked. Specifically, these authors established that the onset of deafness has a significant relationship with the acceptance of and trust in AI-enabled SLI. Prior to Tran et al. (2023) study, Quandt et al. (2022) noted that the adoption and use of AI-enabled SLI is influenced by both the extrinsic and the intrinsic characteristics of the potential users. Other studies, such as those by Abubakar et al. (2025), Kumar Attar et al. (2023), De Meulder (2021) and De Meulder et al. (2024), also identified some pitfalls in the development of AI-enabled SL technologies developed for use among the communities of persons who are Deaf or hard of hearing. In fact, De Meulder et al. (2024) assert that sign language is complex, and SLIs should not be used as the benchmark in the development of AI-enabled SLI. Despite the note of concern raised by De Meulder (2021) and De Meulder et al. (2024) about benchmarking automated sign language translation against human SLIs, the author has yet to find an empirical study that has established the implications of AL-enabled SLI through the perspectives of human sign language interpreters. Hence, this current study.

2.3 Conceptual framework and hypothesis development

The future perspectives of AI-enabled sign language interpretation were probed using the perceived benefits, risks, and trust of AI-enabled SLI. As shown in Fig. 1, the mediating effect of cultural influence on the future perspectives of AI-enabled SLI was also determined in this study.

2.4 Perceived benefits of AI-enabled SLI

In the context of this current study, the perceived benefits are conceptualised as the beliefs of African SLIs about the benefits or positive outcomes of the adoption and use of AI-enabled SLI. Since the introduction of AI into sign language, there have been consistent debates about its potential benefits. For instance, existing studies have noted that the development of AI-enabled SLI has the capacity to foster education and social inclusion and contribute to the elimination of communication barriers in the absence of human SLIs (Brauner et al., 2024; Kahlon & Singh, 2023; Wolfe et al., 2022; Zulu et al., 2025). Other studies, such as those by De Meulder et al. (2024), Kumar Attar et al. (2023) and Quandt et al. (2022), posited that while confidentiality is limited with the presence of human SLIs, the use of AI-enabled SLI enables independence and the autonomy of Deaf users of AI-enabled SL technologies, especially in emergency situations. According to Bragg et al. (2019) and Kahlon and Singh (2023), deployment, acceptance and use of AI-enabled SL translations limits the possibilities of social anxiety among persons who are Deaf or hard of hearing, particularly in an emergency or in a situation where illumination/visibility is so low that accessing the signing frame, facial expressions, gestures and lip movements of human SLIs is difficult. In terms of cost effectiveness, while AI-enabled SL translations may be expensive to acquire, studies have shown that the adoption of such technology is cost effective in the long term (De Meulder, 2021; Zulu et al., 2025). In view of the cost-benefit effect of using automated sign language translation as opposed to human SLIs, Muhammed et al. (2024) and Ong and Ranganath (2005) state that automated SLI could potentially provide a low-cost alternative to traditional sign language interpreters. Regardless of the potential benefits of technology, a few studies have shown that acceptance of emerging technologies can be influenced by cultural differences (Tubadji et al., 2021). In their study, Grassini and Ree (2023) found that the attitudes and perceptions about AI technologies are shaped by cultural backgrounds. Given the foregoing submissions, sign language interpreters with positive attitudes towards AI-enabled SLI may have positive future perspectives regarding AI-enabled SLI. Therefore, it is hypothesized that:

> **H1:** Perceived benefits (PB) will positively predict the future perspectives (FP) of AI-enabled SLI among African SLIs for e-learning purposes.
> **H2:** The perceived benefits (PB) of AI-enabled SLI will have a positive and directed influence on cultural influence.
> **H3:**Cultural influence (CI) will mediate between perceived benefits (PB) of AI-enabled SLI African SLIs and future perspectives (FP) of AI-enabled SLI in Africa for e-learning purposes.

2.5 Perceived risk of AI-enabled SLI

Perceived risk (PR) is described in this study as the subjective perception of potential negative consequences or uncertainty towards the adoption, application, and use of AI-enabled SLI. Despite the proliferation of AI in virtually all sectors, Rohden and Zeferino (2023) indicated that the public still have reservations about the adoption and use of AI. Some studies indicate that the potential risk associated with AI is associated with accuracy, loss of jobs, ethical concerns, loss of privacy, misinformation, and manipulation, among others (Aytekin et al., 2021; Rohden & Zeferino, 2023). Wissing and Reinhard (2018) believe that the perceived risk of AI depends largely on individual differences, but some more recent studies have shown that the perceived risk of AI can be shaped by cultural differences (see: Wang, 2025; Yam et al., 2023). With the influx of AI in SLI, studies have expressed concern about the potential of AI-enabled SLI based on the cultural and linguistic nuances that permeate SL usage across diverse communities of SL users **(**De Meulder, 2021; Muhammad & Sajid Aslam, 2024**).** Many other studies are still **s**keptical about the level of accuracy, the inability of AI to recognise the emotional state of AI-enabled SLI users, and the potential for severe miscommunication in critical situations like medical or legal settings **(**Bragg et al., 2019; Kipp et al., 2011; Muhammed et al., 2024; Ong & Ranganath, 2005; Quandt et al., 2022; Wolfe et al., 2022). SL is not a universal language because it differs from culture to culture. There is thus a need to ascertain the role of CI on the PR of the future of AI-enabled SLI. Therefore, this study proposes that while:

> **H4:** Perceived risks (PR) will predict a positive future perspective (FP) of AI-enabled SLI among African SLIs for e-learning purposes.
> **H5:** Perceived risks (PR) of AI-enabled SLI will have a positive and directed influence on cultural influence.

H6: Cultural influence (CI) will mediate between perceived risks (PR) of AI-enabled SLI African SLIs and future perspectives (FP) of AI-enabled SLI in Africa for e-learning purposes.

2.6 Perceived trust of AI-enabled SLI

In this study, perceived trust (PT) is viewed as the confidence or subjective belief that SLIs have in the reliability and potential of AI-enabled SLI. The level of acceptance, and willingness to adopt and use AI can be influenced significantly by PT (Afroogh et al., 2024). In other words, PT may depend on the emotional state as a crucial determinant of an SLI's willingness to accept the role of AI-enabled SLI and to rely on its use by the communities of persons who are Deaf or hard of hearing. In their study, Othman et al. (2024) noted that trust is a significant factor influencing the acceptance of signing avatar technology rather than human interpreters. However, Othman et al. (2024) and Wasserroth et al. (2025) found that persons who are Deaf or hard of hearing were less likely to trust AI-facilitated sign language interpretation. In some very recent studies, the dynamics of the onset of deafness and the Deaf culture vis-a-vis language abilities were found to influence trust in AI-permeated SL interpretation (Chemnad & Othman, 2025; Imashev et al., 2025). Regardless of the hearing status, Thanetsunthorn and Wuthisatian (2019) assert that perceived trust can be influenced significantly by national culture. Emerging studies have shown that cultural differences have the potential to influence peoples' trust in AI (Chi et al., 2023), but the literature lacks a comprehensive African perspective about the role of cultural influence in the relationship between trust and future perspectives about AI, particularly as it concerns automated SL translation. Therefore, this study proposes that:

H7: Perceived trust (PT) will predict a positive future perspective (FP) of AI-enabled SLI among African SLIs for e-learning purposes.
H8: Perceived trust (PT) of AI-enabled SLI will have a positive and directed influence on cultural influence.
H9: Cultural influence (CI) will mediate between perceived trust (PT) of AI-enabled SLI African SLIs and future perspectives (FP) of AI-enabled SLI in Africa for e-learning purposes.

2.7 Cultural influence (CI) of AI-enabled SLI

Cultural influence (CI) in this study is construed to imply every dimension of belief, customs, knowledge, habits, and morals that informs development, pattern, and use of sign language within a specific community of sign language users. Within the signing communities, culture, geographical locations among other demographic factors have influence the development of group-specific signs and symbols which have most times used to develop national signs. Apparently, based on cultural interferences, sign language difference across Sub-Sahara African countries (Adigun, 2019; Obosu et al., 2023). Thus, it is assumed that based on community norms and ideals of communities of sign language users across different Sub-Sahara African countries, cultural perspectives that shapes sign language usage and patterns may have significant influence on future perspective (FP) of AI-enabled SLI. Although, there is a dearth of research evidence on the relationship between CI and FP but within the behavioural research clusters, CI has been found as an important variable for predicting public judgement and measuring perceptions about how a society evolves and functions (Briley et al., 2014; Dang & Li, 2025; Yam et al., 2023). How people respond to emerging technologies such as AI may be a hidden but important construct in determining how people perceive the adoption and use of AI, especially for communication proposes. In view of the forestated, Dang and Li (2025) remarked that the cultural dimension remains a critical factor in shaping the attitudes, perceptions, and trust in AI systems. Despite Dang and Li's (2025) submission, the cross-cultural research evidence on the future of AI is not all-encompassing and the findings are still inconclusive. For instance, some studies have reported positive predictive capacity of technology based on cultural differences (see: Li et al., 2010; Lin, 2014; Yam et al., 2023). Contrarily, other studies could not ascertain a positive link between cultural influence and the perceived future acceptance and adoption of AI and other technologies (Lin, 2014; Yam et al., 2023). There is thus still fragmented research evidence on the capacity of CI to predict the future acceptance of AI, especially regarding its application for SL communication, so this present study hypothesizes that:

> **H10:** Cultural influence (CI) will positively predict the future perspectives (FP) of AI-enabled SLI among African SLIs for e-learning purposes.

2.8 Method and materials

This quantitative study adopted a descriptive cross-sectional design to advance epistemology about the application of AI-enabled sign language interpretation during online learning programmes for African students who are Deaf or hard of hearing. A purposive sampling technique was adopted to select SLIs who resided and conducted sign language interpretation on the continent of Africa. The study purposively selected members of the Africa Federation of Sign Language Interpreters (AFSLI), a professional body of Sign Language Interpreters in Africa. In addition, a snowball approach was used to further reach out to SLIs who were not on the AFSLI WhatsApp platform but were registered with other National Sign Language Interpreters Associations across different African countries. A total of 412 SLIs from 12 African countries (Egypt, Ghana, Kenya, Lesotho, Liberia, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Zimbabwe) responded to the English language worded e-questionnaire designed with Google Form which were graded on a five point-Likert scale of 5 = Strongly agree, 4 = Agree, 3 = Undecided, 2 = Disagree and 1 = Strongly disagree (See Appendix A). Table 1 presents the distribution of the respondents according to countries.

The 30-item e-questionnaire (Appendix A) consisted of the perceived benefits of AI-enabled sign language interpretation (PB-AI-SLI: 6 items), the perceived risks of AI (PR-AI-SLI: 5 items), the perceived trust in AI-SLI (PT-AI-SLI: 6 items), the effect of cultural influence on AI-SLI (CI-AI-SLI: 7 items), and the future perspectives of AI-SLI (FP-AI-SLI: 6 items). There was no existing scale available to measure the construct of concern in this study, so the research adapted questionnaire items

Table 1 Demographic information of the respondents

Variable		Frequency (%)
Age range	18–24	71 (17.24)
	25–34	114 (27.66)
	35–44	102 (24.76)
	45–54	87 (21.12)
	> 55	38 (9.22)
Years of SLI experience	< 5years	96 (23.30)
	5–10 years	148 (35.92)
	11–15 years	106 (25.73)
	> 15 years	62 (15.05)
Gender	Male	285 (69.17)
	Female	127 (30.83)
Highest educational qualification	Diploma	42 (10.19)
	Bachelor	211 (51.21)
	Masters	152 (36.89)
	Doctorate	7 (1.71)
Living with disability	Yes	13(3.16)
	No	399(96.84)
Do you have family member who requires sign language as a mean of communication	Yes	81 (19.66)
	No	331 (80.34)
Participating countries		
Egypt	16(3.88)	
Ghana	48(11.65)	
Kenya	36(8.74)	
Lesotho	14(3.39)	
Liberia	19(4.61)	
Namibia	22(5.34)	
Nigeria	109(26.46)	
Rwanda	23(5.58)	
Senegal	11(2.67)	
South Africa	47(11.41)	
Tanzania	28(6.80)	
Zimbabwe	39(9.47)	

from literature and similar studies, such as those by Chan and Hu (2023), and Hopcan et al. (2023). In addition, the study collected some demographic information from the study respondents (see: Table 1). The researcher adopted various steps to ensure the validity and reliability of the research instrument. First, he ensured the face and content validity of the questionnaire by conducting a review of it with two professional colleagues who major in language education in a public university in South Africa, and another colleague whose specialty is education evaluation and psychometrics at a private university in Uganda. The comments obtained from their evaluation were appropriately considered before the instrument was further subjected to test of reliability as recommended by Adhikari (2022) (see: method of data analysis) to further determine the suitability of the instrument for structural equation modelling.

2.9 Method of data analysis

The data collected were analysed to establish the relationship between latent and observed variables using a three-fold approach, namely (i) Exploratory Factor Analysis (EFA), (ii) Confirmatory Factor Analysis (CFA), and Partial Least Squares Structural Equation Modelling (PLS-SEM). The use of AMOS and SmartPLS-SEM for data analysis is due to the potentials and drawbacks associated with both statistical packages therefore, specific analytical needs of this study and the features of available software motivated the use of varied software packages (Sarker et al., 2024). According to Hair et al. (2024) and Sarker et al., (2024), SmartPLS-SEM is ideal for exploratory research, theory development and predictive accuracy while AMOS statistical package which employs ML estimating techniques is suitable for theory verification (Brown, 2024; Byrne, 2024; Hair et al., 2010). Specifically, Hair et al. (2024) assert that SmartPLS is advice when analysing complex data set that comprise of formative and reflective construct. Earlier in the study of Ringle, Sarstedt and Straub (2012) SmartPLS has advantages over AMOS because SmartPLS is suitable for the analysis of latent variables. Additionally, Ringle et al. (2015) and Sarker et al. (2024) confirmed that AMOS is more suitable for AMOS for confirmatory analysis and SmartPLS is suited for exploratory analysis. Therefore, this study adopted the strength of both statistical software to achieve a robust result.

Thus, the AMOS v.23 statistical software was used for Confirmatory and Exploratory Factor Analysis respectively to examine and establish the underlying structure of the items on the data collection instrument. The researcher first determined the suitability of the data collected through factor analysis. In line with the recommendation by Shrestha (2021), the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was assessed and observed at 0.65 which obviously exceeded the recommended threshold of 0.60, as stated by Shrestha (2021). In addition, Bartlett's Test of Sphericity was found to be significant (χ^2 = 286.769, df=226, p < 0.001). The foregoing results therefore substantiated the suitability of the data for factor analysis.

The factor analysis process employed principal axis factoring (PAF) as the extraction method, based on eigenvalues > 1. Five factors [cultural influence (CI), future perspectives (FP), perceived benefits (PB), perceived risks (PR), and perceived trust (PT)] were obtained and retained, based on the forestated benchmarks. Together, the five factors accounted for 67.4% of the total variance. The oblique (Promax) rotation was then applied to ensure a decline of multiple indicators into smaller sets of interpretable factors. As revealed on Table 2, the rotated factor matrix showed that the items were strongly loaded (> 0.50) on their respective factors. Kindly note that some items of Appendix A (CI7, FP3 and FP6) were dropped after the EFA computa-

Table 2 A five-factor Pattern Matrix[a] obtained through the EFA

	Factor				
	1	2	3	4	5
PB1			0.909		
PB2			0.910		
PB3			0.663		
PB4			0.574		
PB5			0.665		
PB6			0.888		
PR1				0.851	
PR2				0.673	
PR3				0.801	
PR4				0.806	
PR5				0.910	
PT1		0.867			
PT2		0.915			
PT3		0.646			
PT4		0.752			
PT5		0.859			
PT6		0.640			
CI1	0.590				
CI2	0.977				
CI3	0.934				
CI4	0.831				
CI5	0.554				
CI6	0.988				
FP1					0.746
FP2					0.632
FP4					0.958
FP5					0.801

a. Rotation converged in 6 iterations

tion because of low factor loading of <0.5 (See Table 2). According to Güvendir and Özkan (2022), removal of test items with low factor loading helps to improve statistical reliability, validity, and interpretability of research instruments. The five-factor loaded structure was then subjected to confirmatory factor analysis (CFA) and Structural Equation Modelling (SEM) using the Partial Least Squares Structural Equation Modelling (PLS-SEM), known as the SmartPLS 3 statistical software, to test the hypothesised model (See Fig. 1).

A Confirmatory Factor Analysis (CFA) was also conducted to test the fitness of the established data into the hypothesised model, and the SPSS AMOS v.23 software was used to validate the proposed five-factor model, comprising CI (6 items), FP (4 items), PB (6 items), PR (5 items), and PT (6 items). The linearity, multicollinearity, normality, and potential outlier assumptions in the dataset were ascertained and established before conducting the CFA, as recommended by Adhikari (2022), Bansal and Singh (2023), and Schmidt and Finan (2018). When conducting the CFA, the Maximum Likelihood Estimation method was applied and various statistical measurement pointers were used, namely the Chi-Square Test (χ^2), the Comparative Fit

Index (CFI), the Goodness of Fit Index (GFI), the Normed Fit Index (NFI), the Root Mean Square Error of Approximation (RMSEA), the Tucker Lewis Index (TLI). The model demonstrated good fit, and the data were found to be within the recommended threshold at χ^2 (314) = 799.923, $p < 0.001$, χ^2/df = 2.54, CFI = 0.94, NFI = 0.91,TLI = 0.90, RMSEA = 0.054, GFI = 0.89, in line with the assumptions and rules guiding the use of the CFA (Adhikari, 2022). To achieve the good fit of the instrument in the computation of CFA, the study followed the recommendation of Tavakol and Wetzel (2020) as well as Tang et al. (2025). Therefore, Item PB2, PT1, PT4, PT5, CI2, and CI6 respectively were dropped because the items indicated weak relationship between observed indicators and latent factor. Apparently, item deletion in the process of conducting the EFA and CFA were empirically and theoretically driven as indicated in the studies of Chan and Lay (2018), Güvendir and Özkan (2022), Hair et al. (2019), Tavakol and Wetzel (2020) as well as Tang et al. (2025).

The researcher used the Partial Least Squares Structural Equation Modelling (PLS-SEM) to test the hypothesised model and establish the relationships between the exogenous variables (PB, PR and PT) and the endogenous (FP) latent variables using the validated items (See Appendix B). Studies have established the potency of the Partial Least Squares Structural Equation Modeling (PLS-SEM) as a statistical approach that provides robust opportunities for social science research when analysing and interrogating the complex relationships between latent variables and observed variables (Edeh et al., 2023; Hair et al., 2021). Hair et al. (2021) affirmed the potency of the PLS-SEM for research that analyses complex models, makes predictions, and provides explanations of the complex structure of variables or when developing a theory. In the process of estimating the relationships, the PLS-SEM combines a measurement model and a structural model to estimate relationships simultaneously, making it a popular alternative to covariance-based SEM (Dash & Paul, 2021). Compared to the SPSS AMOS statistical software, the PLS-SEM has become a widely acceptable multivariate analysis technique used by researchers in the social sciences (Dash & Paul, 2021; Hair et al., 2018).

Unlike the SPSS AMOS statistical software, there are many levels of equations involved when using the PLS-SEM for model development and provision of the required explanations. The modelling procedures include model specification, a measurement model, and a structural model. Model specification involves estimation of the parameters, such as factor loadings, and re-specification of the model based on model fit and parameter interpretation (Hair et al., 2019; Ringle et al., 2020; Sarstedt et al., 2019). This study then proceeded with the sub-models, that is, the measurement and structural models to address and analyse the data. The measurement model presented information on the factor loading, Average Variance Extracted, Composite Reliability, Cronbach's alpha, and cross-loading of the five factors (PB, PR, PT, CI, and FP). The structural model showed the relationships between the latent and observed variables using path coefficients. The significance level of the model was achieved with bootstrapping at 5000, which is the standard and recommended practice for robust statistical analysis (Hair et al., 2019), and the explanatory power of the hypothesised model was established through adjusted R-square and effect size.

2.10 Ethical consideration

This study was conducted in strict compliance with ethics of social science research. The conduct of this study was in accordance with the conduct of social and humanities research of the University of Namibia, Namibia with approval number 2025/RU 23/004/53. Imperatively, the study adhered to ethical principles for social science research as indicated in the *Declaration* of *Helsinki.* Thus, participation in the study was voluntary and all participants selected for the study provided a written informed consent before participation in the study was voluntary. Participants were assured of their confidentiality and were informed that data obtained was for research purposes alone. Participants were assured of protection of their data which would only be for research purposes.

2.11 Common method bias

Common method bias (CMB) occurs when the construct variables in the study are measured through similar response formats, which was the case in this current study. According to Conway and Lance (2010), such similarities remain a threat to the integrity of study results and such threats must be eliminated. The Harman's single-factor test was thus conducted to provide a further basis for the accuracy and validity of the results, as advised by Podsakoff et al. (2024). The report of the Harman's single-factor test conducted did not detect CMB. An unrotated factor analysis of all the items revealed multiple factors, with the first factor accounting for 16.6% of the variance, which is below the 50% threshold (Podsakoff et al., 2024). Therefore, it was unlikely that CMB occurred and created a concern in this study.

As shown on Table 1, of the 412 participants, a total of 114 (27.66%) were between the ages of 25 and 34 years and they formed the largest cohort of study participants. This was followed by those between the ages of 35 and 44, who comprised 24.76% of those who responded to the research instrument. A few (9.22%) SLIs above the age of 55 also participated in this study. While those with 5 to 10 years of work experience formed the largest group of study participants (35.92%), only 1.71% of the 412 participants had a doctorate as their highest educational qualification. Only 3.16% of the study participants indicated that they were living with disabilities, and about 81(19.66%) responded that they had family members who required sign language for communication purposes. A total of 109 SLIs from Nigeria which represents about 26.46 of the total respondents were from Nigeria. The higher percentage of respondents from Nigeria can be linked to the populations of Deaf and hard of hearing and longstanding history of Deaf education in Nigeria (Shemang, 2016; Treat, 2016). Additionally, 48(11.65%) and 47(11.41%) respondents emerged from Ghana and South Africa while the population of SLIs who responded to the research instrument from Zimbabwe and Kenya were 39(9.47%) and 36(8.74%). Only 2.67% of the study respondents were from Senegal.

Majority of those who responded to the research instrument were males, and they represented 69.17% of the respondents. Interestingly, while literature have substantiated the fact that there were more female as Sign Language Interpreters (Brien, Brown & Collins, 2004; Mapson, 2014; Napier et al., 2022) but those who responded to the research instrument for this study were largely males. Although, gender proportion in this study that involved more males to females does not correspond to existing evidence in existing research such as (Becker, 2022), Jackson et al. (2021) and Smith (2008) which showed that male were less inclined to respond to online surveys than females but studies of Göritz and Stieger (2009) as well as SlausonBlevins and Johnson (2016) stated that response to online surveys in relation to gender differences is a function of motivation. In fact, Smith (2008) posited that response to online surveys is a determinant of values that either of the genders attribute to the study. Therefore, it can be assumed that higher response obtained from male sign language interpreters can be linked to values attributed to dynamics, application, and use of artificial intelligence which have male dominance as found in the studies of Møgelvang et al. (2024), Otis et al. (2024), and Russo et al. (2025) (Fig. 2).

3 Results

The presentation of the Structural Equation Modelling (SEM) is incomplete without discussing the two key components that make the SEM a unique statistical approach that is widely used among behavioural and social science researchers when analysing complex relationships among variables (Hair et al., 2018). The two pivotal components of the SEM are (i) the measurement Model and (ii) the structural Model. These two models are distinct but interconnected and serve to analyse the latent constructs and their relationships. The results of this study will be presented based on the two pivotal components of the SEM.

3.1 Measurement model

Three major criteria were used to determine and ascertain the construct reliability and validity, as shown on Table 3. The criteria were composite reliability (CR), Cronbach's alpha (a), and the average variance extracted (AVE), as suggested by Hair et al. (2017, 2019; 2022) as a rule of thumb. Most of the items had outer loadings of ≥ 0.70, which Hair et al. (2017) adjudged as ideal and representative of a strong indicator. However, some of the factors, namely PB2, PT1, PT4, PT5, CI2, CI6, and CI7, loaded below 0.60. Two factors (PT4 and PT5) were removed because their presence negatively influenced the value of the composite reliability (CR) and the AVE to fall below 0.50. PB2, PT1, PT4, PT5, CI2, CI6, and CI7 failed to agree with the rule of thumb (Chan & Lay, 2018; Hair et al., 2019) and they were considered unreliable for measuring the constructs. In other words, these unreliable items were excluded from the final structural model. Following removal of the unreliable items, the PB, PR, PT, CI, and FP constructs had evaluated CR and AVE values (See Table 3). The values of the CV (above 0.70) and the AVE (above 0.60) corresponded with the values benchmarked by Dash and Paul (2021), Fornell and Larcker (1981), and Sarstedt et al. (2019). The five constructs of cultural influence (CR = 0.892; AVE = 0.674), future perspectives (CR = 0.901; AVE = 0.698), perceived benefits (CR = 0.892; AVE = 0.674), perceived risk (CR = 0.925; AVE = 0.713), and perceived trust (CR = 0.856; AVE = 0.667) met the acceptable criteria for establishing convergent validity, as shown on Table 3.

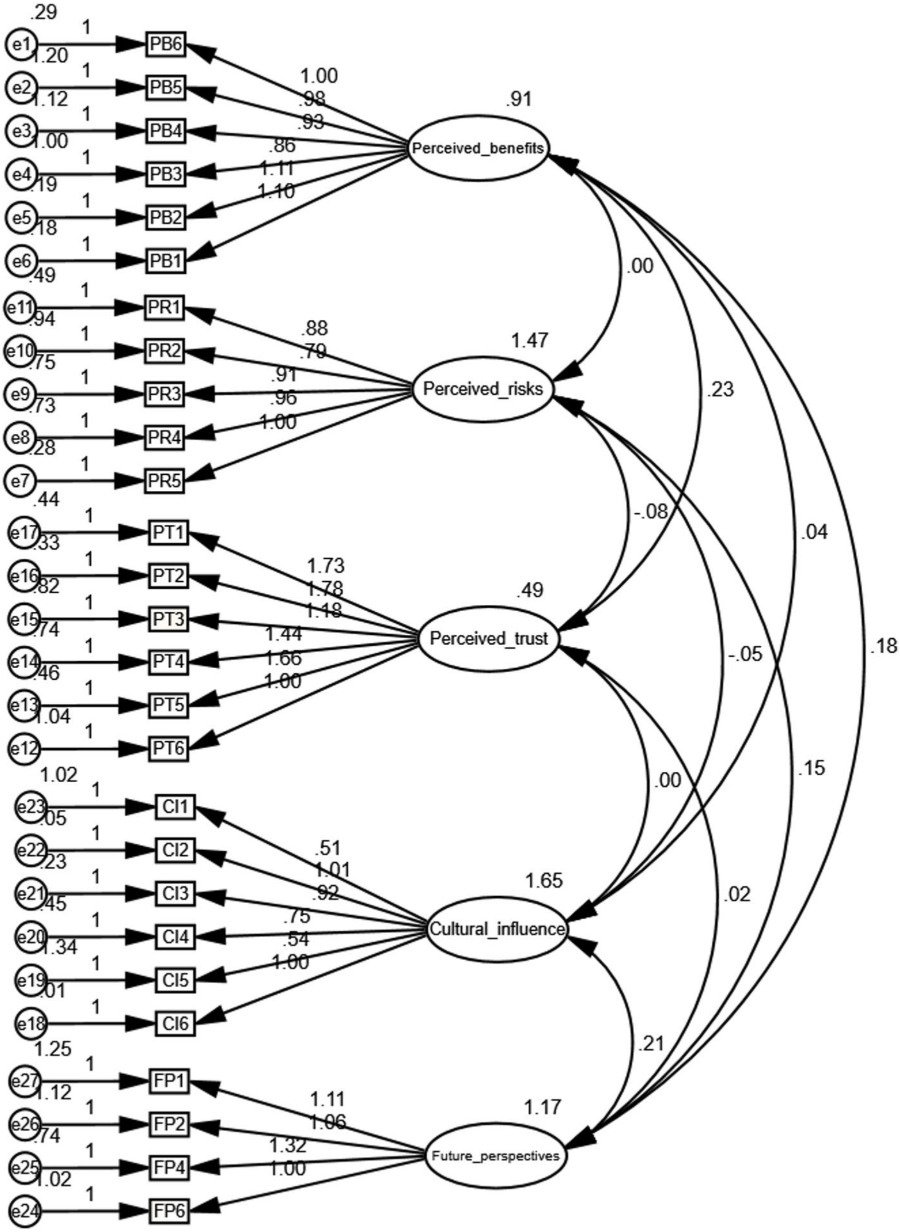

Fig. 2 CFA output showing loadings of the constructs

The discriminant validity of the items was established using the cross-loading output. Discriminant validity refers to an approach that is used to establish that items are unrelated concepts and not highly correlated (Hair et al., 2017). It is important to determine the discriminate validity of the constructs because this helps to avoid misinterpretation of the results by showing that the effects observed are not influ-

Table 3 Convergent validity and reliability of the constructs

Item	Outer loadings	VIF	Composite reliability (CR)	Average variance extracted (AVE)
Perceived benefits (Median = 0.178; Cronbach's Alpha = 0.884)			0.892	0.674
PB1	0.946	3.197		
PB3	0.831	1.871		
PB4	0.637	1.988		
PB5	0.859	1.721		
PB6	0.720	2.990		
Perceived risks (Median = 0.170; Cronbach's Alpha = 0.905)			0.925	0.713
PR1	0.818	3.038		
PR2	0.859	1.918		
PR3	0.800	2.582		
PR4	0.825	2.695		
PR5	0.909	2.216		
Perceived trust (Median = 0.257; Cronbach's Alpha = 0.785)			0.856	0.667
PT2	0.644	3.261		
PT3	0.732	2.144		
PT6	0.946	1.546		
Cultural influence (Median = 0.208; Cronbach's Alpha = 0.844)			0.892	0.674
CI1	0.764	1.852		
CI3	0.868	2.585		
CI4	0.836	2.750		
CI5	0.815	1.526		
Future perspectives (Median = 0.249; Cronbach's Alpha = 0.858)			0.901	0.698
FP1	0.799	2.128		
FP2	0.818	1.558		
FP4	0.895	3.279		
FP5	0.832	2.479		

enced by the confounding variables (Schriesheim & Cogliser, 2009). Cross-loadings of the items (Table 4) showed that each measurement item had its highest loading on its intended construct. As indicated by Fornell and Larcker (1981) and Henseler et al. (2015), compared to all other constructs, the indicators were expected to load highest on their assigned constructs, and these indicators' values are shown in bold on Table 4. In addition to the cross-loading values, the Fornell-Larcker criterion was also presented, as the use of the Fornell-Larcker criterion (see Table 5) and examination of the cross-loadings together formed a formidable approach to evaluating and establishing the discriminant validity (Henseler et al., 2014, 2015; Rönkkö & Evermann, 2013). In view of the values obtained on Tables 4 and 5 for the cross-loading and the Fornell-Larcker criterion, the constructs are vividly distinctive from the other

Table 4 Cross loading of the construct in the model (Discriminant validity)

	Cultural influence	Future perspectives	Perceived benefits	Perceived risk	Perceived trust
CI1	0.784	−0.054	0.019	0.212	0.187
CI3	**0.852**	0.069	−0.058	0.009	0.234
CI4	**0.827**	0.066	−0.053	0.005	0.192
CI5	**0.820**	0.000	−0.240	0.153	0.204
FP1	0.087	**0.771**	0.159	0.068	0.044
FP2	−0.045	**0.826**	0.262	0.187	0.217
FP4	−0.016	**0.893**	0.187	0.093	0.139
FP5	0.098	**0.827**	0.063	0.264	0.140
PB1	−0.119	0.123	**0.863**	−0.034	0.186
PB3	−0.168	0.153	**0.832**	−0.109	0.027
PB4	−0.064	−0.023	**0.633**	−0.005	0.355
PB5	−0.049	0.267	**0.860**	0.096	0.033
PB6	−0.051	0.001	**0.717**	0.022	0.180
PR1	0.138	0.084	−0.043	**0.823**	0.016
PR2	0.068	0.291	0.012	**0.853**	−0.014
PR3	0.106	0.029	−0.110	**0.805**	0.071
PR4	0.107	0.082	−0.021	**0.828**	0.110
PR5	0.140	0.178	0.039	**0.910**	0.086
PT2	0.136	0.016	0.182	−0.074	**0.746**
PT3	0.174	0.044	0.135	−0.045	**0.770**
PT6	0.255	0.257	0.024	0.123	**0.922**

Table 5 Fornell-Larcker criterion (Discriminant validity)

	Cultural influence	Future perspectives	Perceived benefits	Perceived risk	Perceived trust
Cultural influence	0.821				
Future perspectives	0.021	**0.830**			
Perceived benefits	−0.125	0.215	**0.780**		
Perceived risk	0.126	0.200	−0.008	**0.844**	
Perceived trust	0.249	0.185	0.096	0.051	**0.817**

constructs in the model. Thus, the data is reliable and valid because it exhibited discriminant validity.

3.2 Structural model

This study considered the implications of collinearity, path coefficients, effect size (F^2), predictive relevance (Q^2), and R square of endogenous variables in developing the structural model. Collinearity was addressed using the values of the variance inflation factor (VIF). The values obtained for the VIF fell below the threshold of 3.3, as recommended by Diamantopoulos and Siguaw (2006) and Hair et al. (2011). Hence, the study can confirm that multicollinearity was not a concern as the values of the VIF in this study ranged between 1.526 and 3.279, as shown on Table 3. In addition, the bootstrap analysis with 5000 subsamples was used to determine the path coefficients, t-statistics, and p-values. The coefficient of determination (R^2) was calculated to determine the in-sample predictive capacity of the endogenous variables. As posited by Sainani (2014), it is important to evaluate a structural model based on its explanatory capacity. In view of the foresaid by Sainani (2014), Table 6 reveals that the R^2 value of 0.097 was computed for CI, which accounted for 9.7% of the variation observed in the FP. Therefore, the model can be said to have a small-moderate level of explanatory strength for explaining the latent variables in the model. Additionally, the magnitude of the effect, that is the effect size (f^2) of the study sample, was determined based on the classification of small = 0.02, medium = 0.15, and large = 0.35), as advanced by Cohen (1988) and Hair et al. (2019).

In establishing the explanatory strengths of the exogenous variables and the endogenous variables, this study showed that the model revealed a small explanatory capacity. PB -> CI was confirmed with an explanatory effect value (f^2) of 0.024. Similarly, PB -> FP, PR -> CI, PR -> FP all exhibited small explanatory abilities, with explanatory effect values (f^2) of 0.043, 0.014, and 0.042 respectively. Table 6 shows that the explanatory effect value (f^2) of PT -> CI was 0.072 and PT -> FP also accounted for a small explanatory ability, with a 0.072 explanatory effect value (f^2). Therefore, this study asserts that the exogenous variables (PB, PR and PT) have relatively small explanatory capacities, which can provide an explanation for the FP in the model (see Fig. 3). On the other hand, CI -> FP had no explanatory ability as the value of f^2 was 0.000. PB -> CI-> FP; PR -> CI-> FP; and PR -> CI-> FP had no indirect explanatory abilities as they were found to have an explanatory effect value (f^2) of 0.000 for the model in Fig. 3. The finding implies that PB, PR and PT through CI does not provide any explanation for how African SLIs perceived the implication of technology on the use of AI-enabled SLI, particularly OdeL programmes. Further, in line with the position of Chin (1998) and Hair et al. (2017), the predictive significance (Q^2) of the model was assessed through an omission distance of 7, using the blindfolding process (Hair et al., 2017). The process found that the Q^2 of the exogenous variable was greater that zero, but not high to the extent that Q^2 could be said to have a large predictive relevance for the endogenous constructs. As shown

Table 6 Standardized path coefficient for tested model

Hypothesis	Path link	β	t-statistics	*p*-values	Remarks	f^2	Effect
	CI -> FP	−0.019	0.342	0.733	Not Accepted	0.000	None
	PB -> CI	−0.149	2.546	0.011	Accepted	0.024	Small
	PB -> FP	0.198	2.815	0.005	Accepted	0.043	Small
	PR -> CI	0.112	1.836	0.066	Not Accepted	0.014	Small
	PR -> FP	0.196	3.794	0.000	Accepted	0.042	Small
	PT -> CI	0.258	6.217	0.000	Accepted	0.072	Small
	PT -> FP	0.160	2.540	0.011	Accepted	0.072	Small
	PB -> CI-> FP	0.003	0.311	0.756	Not Accepted	0.000	None
	PR -> CI-> FP	−0.002	0.282	0.778	Not Accepted	0.000	None
	PT -> CI-> FP	−0.005	0.336	0.737	Not Accepted	0.000	None
		R^2	Q^2 (=1-SSE/SSO)				
	CI	0.097	0.058				
	FP	0.111	0.064				

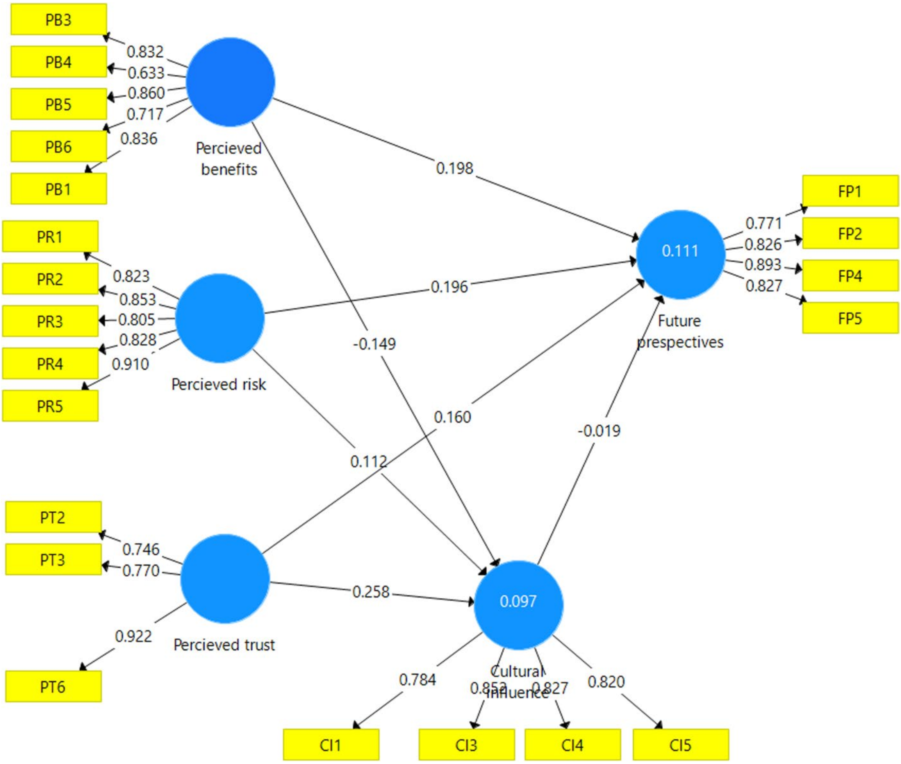

Fig. 3 Structural model

on Table 6, both cultural influence ($Q^2 = 0.058$) and future perspectives ($Q^2 = 0.064$) demonstrated a small Q^2.

As shown on Table 6, PB ($\beta = 0.198$, $p = 0.005$), PR ($\beta = 0.196$, $p = 0.000$) and PT ($\beta = 0.160$, $p = 0.011$) had a significant positive relationship with FP. On the other hand, CI had no direct predictive capacity for FP of AI-enabled SLI by the study participants. In terms of a direct relationship with CI, it was found that PB ($\beta = -0.149$, $p = 0.011$) had a direct and negative relationship with CI while PT ($\beta = 0.258$; $p = 0.000$) had a direct and positive relationship with CI. However, despite having a small effect size ($\beta = 0.112$, $p = 0.066$), PR had no link with CI in reference to AI-enabled SLI. Table 6 shows that CI had no significant predictive influence between the PB ($\beta = 0.003$; $p = 0.756$), PR ($\beta = -0.002$; $p = 0.778$), and PT ($\beta = -0.005$; $p = 0.737$) and FP about AI-enabled SLI among African SLIs. This reveals that hypotheses H1, H2, H4, H7, and H8 were supported, while hypotheses H1a, H3, H5, H6, H9 and H10 were not supported.

The study found that the future perspectives of AI-enabled SLI were significantly predicted by PR, followed by PB and PT respectively. However, PR, PB and PT has small explanatory capacity of 0.043, 0.042 and 0.072 respectively which indicate that the exogenous latent variables have a low practical importance to the predictive power. In other word, exogenous latent variables have a weak and limited contribution to the explanation of the variance of the endogenous variable (FP). The foregoing supports the research proposition that African SLIs may have a positive disposition towards AI-enabled SLI if there are only minimal errors with it. However, there was an associated negative but significant prediction of how African SLIs perceived the future of AI-enabled SLI. This may imply that, despite having come to terms with the realisation that automated SLI has crept into sign language, the participants do not totally trust the potency of AI-enabled SLI. This finding may have implications for online learning programmes that wish to integrate AI-enable SLI, sign language professionals, researchers in Deaf education and Deaf studies, and software developers. Developers must focus on achieving comprehensive synergy between all stakeholders in the development of responsive AI-enabled SLI for use by students who are Deaf or hard of hearing for online pedagogies.

4 Discussion

The communication challenges among students who are Deaf or hard of hearing is a long-standing issue which constantly generates concern among the relevant stakeholders (Adigun, 2019; Marschark et al., 2006; Obosu et al., 2023). Sign language and sign language interpreters have helped to foster communication between the students who are Deaf or hard of hearing, their hearing peers, and their teachers, especially in their physical classrooms (Adigun, 2019; Marschark et al., 2005; Napier & Barker, 2004). The inclusion of students who are Deaf or hard of hearing in e-learning environments where teachers, students who are Deaf or hard of hearing, and their SLIs are separated by geographical space has, however, been found to be problematic for all involved (Adigun et al. 2022a, b, 2023; Marschark et al. 2005; Ngubane and Adigun 2024). The need for the physical presence of sign language interpreters has been found challenging, especially in emergency situations that may arise due to public health concerns, natural disasters, civil unrest, and personal medical emergencies, among others (Adigun et al. 2021, 2022a, b; Kaviyaraj et al., 2021; Roman et al., 2023). The development and application of AI-enabled SLI has thus been put forward to advance seamless and timely communications for the students who are Deaf or hard of hearing as it does not require the physical presence of SLIs.

There have been various discussions around the development, application, and use of AI-enabled SLI in recent times (Bragg et al., 2021; Wolfe et al., 2022), but such discourses have largely been among linguists, software developers, and computer scientists, with little involvement of persons who are Deaf or hard of hearing (De Meulder, 2021; Kipp et al., 2011). There are currently no published research studies that have assessed the concerns or views of SLIs about the introduction of AI-enabled SLI for deployment and use for online learning engagements. This study has thus bridged this existing research gap by determining the perception of African SLIs about AI-enabled SL for e-learning engagements.

In this study, the result of the SEM analysis showed that PB, PR and PT all had a significant positive prediction for future of AI-enabled SLI. Skepticism towards new technology has been echoed for several decades. In fact, Davis (1986), in his Technology Acceptance Model, and Adigun et al. (2025) assert that perception about adoption and use of new technologies is directly proportional to personal beliefs about technological performance. This belief does not account for the implications of the perceived risks associated with the deployment and use of such technologies. Such perception about the potential benefits, risks, and perceived trust associated with new technologies such as the AI-enabled SLI, was found to influence the perceived future acceptance or use of AI-enable SLI among some African SLIs. This finding is consistent with the findings of Aytekin et al. (2021), De Meulder (2021), De Meulder et al. (2024), Kumar Attar et al. (2023), Rohden and Zeferino (2023), and Tran et al. (2023). Some earlier studies have shown that the potential pitfalls of automated SLI remain a factor that shapes the perspectives of professional SLIs about AI-enabled sign language (Bragg et al., 2019; De Meulder et al., 2024; Kipp et al., 2011; Muhammed et al., 2024; Rohden & Zeferino, 2023).

Wissing and Reinhard (2018) believe that the perceived risk of AI depends largely on individual differences, but this study found that trust is an important factor that determines how African SLIs perceive the future of AI-enabled SLI. In other words, the participants of this study seem to have some level of confidence in the reliability and potentials of AI-enabled SLI. The findings therefore corroborate the earlier submissions by Afroogh et al. (2024) and Othman et al. (2024). Othman et al. (2024) state that perceived trust in AI is directly proportional to how an individual or organisation accepts, adopts, and deploys AI for use. This implies that while the study participants appreciated the potential advantages presented by AI-enabled SLI, their optimism about the future of AI-enabled SLI for use by students who are Deaf or hard of hearing in an online learning environment is situated in the belief of plausible advancement of unresisted access to e-education by students who are Deaf or Hard of hearing. The association between PB and FP of AI-enabled SLI provides clear evidence of an on-going shift in the perceived potential danger and heightened potential threats associated with use AI-enabled SLI (Ngubane & Adigun, 2024).

However, the small effect size obtained for PB, PR, and PT towards FP of AI-enable SLI indicate that the three exogenous latent variables have a low practical explanatory capacity to holistically explain FP of AI-enable SLI. While the small effect size may have direct consequences for the explanation of FP of AI-enable SLI as posited by Funder and Ozer (2019); Gelman and Carlin (2014) and Goetz et al. (2012) and Primbs et al. (2023) who caused on total reliance on the use of effect size in the generalization of empirical findings. Agreement with Primbs et al. (2023) is because sign language is dynamic across communities and nations of Africa, thus, cultural factors that shape the development and use of sign language among communities of sign language users, national educational and technological policies, ethical dilemmas, potential job displacement, digital divide and infrastructural provision among other contextual factors may further explain FP of AI-enabled SLI among African Sign language interpreters.

Regardless of any contextual factors such as cultural implication, the participants of this study were positive about the advantages of AI-enabled SLI. Therefore, the findings of this study corroborate the results of the existing studies that indicate that automated SLI is highly likely to foster the achievement of social inclusion, social awareness, and reduction of social anxiety by eliminating communication and information challenges that may be observed with the physical absence of human SLIs (see: Bragg et al., 2019; De Meulder et al., 2024; Kahlon & Singh, 2023; Kumar

Attar et al., 2023; Ngubane & Adigun, 2024; Quandt et al., 2022; Wolfe et al., 2022; Zulu et al., 2025).

Furthermore, the SEM analysis revealed that there is no direct predictive capacity of CI on FP about AI-enabled SLI by the study participants but direct relationship between PB and PT with CI was established. The observed positive relationships could be attributed to enhance public awareness or professional knowledge about psychosocial needs of the students who are Deaf or hard of hearing, equal communication rights, inclusivity, and social justices. Further, the findings indicate that cultural values and norms shape African SLIs' perceived benefits and trust in AI-enabled SLI. In other words, African SLIs with cultural beliefs that accommodate and prioritise educational advancement of students who are Deaf or hard of hearing would have greater affinity for the acceptance of AI-enabled SLI (Grassini & Ree, 2023; Othman et al., 2024; Tubadji et al., 2021). However, such cultural influence does not shape individuals' trust about the functionality of AI-enabled SLI. The findings of this study align significantly with the reports provided by Chi et al. (2023) and Thanetsunthorn and Wuthisatian (2019). The implications of the findings in terms of the insignificant link between trust and cultural influence are that participants' trust is technology driven rather than being driven by cultural belief system or values. More importantly, culture does not shape trust in the accuracy and reliability of AI-enabled SLI.

5 Conclusion and recommendation

This study has brought forward the perspectives of African sign language interpreters into the discourse of artificial intelligence in sign language communication. The study established the future orientation of AI-enabled SLI for deployment in online learning environments, as perceived by professional sign language interpreters from the continent of Africa. Their perspectives are shaped by potential benefits, trust, and risks, rather than by cultural inferences. This study noted that there is a small explanatory capacity of perceived benefits, trust, and risks on future perspectives of AI-enabled SLIs. However, several other conceptual factors such as national educational and technological policies, ethical dilemmas, potential job displacement, digital divide and infrastructural provision may have greater effect and explanatory power to explain future perspectives of AI-enabled SLI among African SLIs. The findings established in this study therefore highlight the emerging debates about the capacity of AI-enabled SLI to provide uniformity to its users when sign language itself is not universal. Sign language is a complex and diverse language, and its structure is defined by cultural demands (Adigun, 2019; De Meulder et al., 2024). Every country has a specific sign language, and each country's ethnicities and languages of the communities shape the respective sign languages.

It is thus crucial that programmers and software developers in the AI-enabled sign language projects work synergistically with professional sign language interpreters and the community of students who are Deaf or hard of hearing to improve on the functionality of reliable real-time interpretation, transparency, and user experience of AI-enabled SLI. The need for high accuracy of the AI-enabled SLI cannot be overemphasised; therefore, developers should ensure high-definition performance that is user-friendly while safeguarding against ethical dilemmas. While continued role of human SLIs in safeguarding cultural and linguistic nuances of sign language cannot be over emphasised, there is need to develop and strengthen AI-mediated sign language policies and regulatory frameworks that does not only ensure ethical use of AI-enabled sign language interpretations but also accuracy and accountability of AI-mediated sign language interpretation. Relevant policies should foster hybrid model of AI-enabled sign language interpretation with recurrent oversight management by professional sign language interpreters. Therefore, the need to invest in Sign language interpreter education and training that is embedded in the application of digital infrastructure becomes necessary. Teachers and educational instructors for students who are Deaf or hard of hearing should be adequately trained on how to effectively integrate AI-enabled sign language interpretation into teaching and learning activities to ensure that students remain responsive to instructional deliveries.

6 Limitation of the study and future research

One major shortcoming of this current study is the lack of qualitative datasets. More qualitative data could provide interesting information that would assist in shedding light on the development and application of AI-enabled SLI. In addition, limited research into SLI, technology-enhanced sign language interpretation and or how culture influence sign language among researchers from the Sub-Sahara African sub-region limits extensive literature reviewed in this study. The researcher acknowledged that the use of single dataset for exploration and confirmation which was used in this study can capitalize on chance and blur the distinction between model generation and model testing as stated by Kline (2023). Therefore, future studies of this nature particularly among SLIs should endeavour to ensure that exploration and confirmation dataset should be conducted on a separate study participant. Establishment of discriminant validity in the study relied on cross-loadings and Fornell-Larcker for discriminant validity, and on Harman's single-factor test for common method bias whereas studies of Henseler et al. (2015) and Podsakoff et al. (2003) have both revealed that such approach has weak diagnostic for method bias. Therefore, it is suggested that future studies should endeavor to report HTMT values (and thresholds) for the constructs. Such studies should as well add a fuller CMB diagnostic beyond Harman's test. Also, variations in the perceptions of the participants based on their demographic profiles were not ascertained in this study. In fact, gender differences, that is proportion of males to females remain a concern which should be well managed in future studies. Exclusion of Deaf or Hard of hearing and AI developers, and absence other relevant stakeholders as student participant is a significant limitation to robust findings that is critical to the perceptions about AI-enabled SLI for deployment in e-learning activities that involves students who are Deaf or Hard of hearing. While this study adopted a descriptive cross-sectional research design, should approach similar studied with a multi-stakeholder participant with a data collection process that will involve a mixed-method approach.

Appendix A

Questionnaire on AI-Enable Sign Language Interpretation

Dear respondents,

Thank you for agreeing to respond to the items of this questionnaire. Kindly note that this questionnaire is basically for research purposes and your response will be treated confidentially. The study was a result of my curiosity to ascertain if AI-enabled sign language interpretation can resolve challenges faced by deaf students in online learning. Your response as human sign language interpreters will be useful.

Thank you.

This is a five-response format questionnaire where SA = Strongly agree, A = Agree, U = Undecided, D= Disagree and SD = Strongly disagree. Kindly tick ( ) as appropriate to you.

	Perceived benefits of AI-enabled sign language interpretation (AI-SLI)	SA	A	U	D	SD
PB1	AI-SLI can increase efficiency online education for deaf students.					
PB2	**AI-SLI** can offer convenience and save time in online teaching.					
PB3	**AI-SLI** can improve lecturer-deaf students' interactions during online learning processes.					
PB4	**AI-SLI** can help solve complex sign language vocabularies.					
PB5	**AI-SLI** can lead to cost savings than using human signers.					
PB6	**AI-SLI** can create new opportunities for learning in virtual classrooms.					
	Perceived Risks of AI					
PR1	**AI-SLI** may lead to expanded traumatic episodes among deaf students in virtual classrooms.					
PR2	**AI-SLI** may violate privacy concerns of teachers and students in virtual classrooms.					
PR3	Using **AI-SLI** will not be able to respond to educational needs of deaf students in virtual classrooms.					
PR4	**AI-SLI** may perpetuate bias and discrimination for deaf students in virtual classroom.					
PR5	**AI-SLI** may have unintended consequences for deaf students in virtual classroom.					
	Perceived Trust in AI					
PT1	I trust **AI-SLI** to perform required sign language tasks accurately.					
PT2	I trust **AI-SLI** to make reliable instructional decisions.					
PT4	I believe **AI-SLI** is predictable and can be manipulated for the benefits of sign language tasks.					
PT4	I have confidence in **AI-SLI**' ability to learn new sign language and model.					
PT5	I trust AI to be used ethically in inclusive and responsive to deaf students' use in open and distance learning programmes.					
PT6	I trust **AI-SLI** can supersede the efforts of human signers.					
	Cultural influence on AI-SLI					
CI1	My cultural perspective of variations in sign language influences my attitudes towards **AI-SLI**.					
CI2	Different cultural dispositions and associated cultural influences is not in favour of **AI-SLI**.					
CI3	**AI-SLI** development should take cultural differences into account.					

	Perceived benefits of AI-enabled sign language interpretation (AI-SLI)	SA	A	U	D	SD
CI4	Different cultures may have different perceptions of **AI-SLI**.					
CI5	**AI-SLI** development should take cultural differences into account.					
CI6	My cultural and professional belief is not in favour of **AI-SLI**.					
CI7	Cultural diversity can bring unique perspectives to the development and use of **AI-SLI**.					
	Future perspectives					
FP1	I believe **AI-SLI** is the future for deaf education particularly in the open distance learning programmes.					
FP2	I believe **AI-SLI** is the end of physical interaction between human sign language interpreters and deaf students.					
FP3	I am optimistic about the future of **AI-SLI** will reduce the existence of human signers.					
FP4	**AI-SLI** could eradicate empathy received by deaf people					
FP5	**AI-SLI** would enhance the individualized instruction and self-directed learning					
FP6	**AI-SLI** will facilitate independent living					

Demographic Information

1. **What is your age range?** (18-24, 25-34, 35-44, 45-54, 55+)
2. **Nationality…**……………………………………………………………
3. **What is your occupation/field of study?** ________________
4. **How long have you been in your profession?**__________
5. **What is your level of education?** (High School, NCE, Bachelor's, Master's, PhD)
6. **What is your gender?** (Male, Female)
7. **Are you D/deaf or non-D/deaf**

Appendix B

Questionnaire on AI-Enable Sign Language Interpretation

Dear respondents,

Thank you for agreeing to respond to the items of this questionnaire. Kindly note that this questionnaire is basically for research purposes and your response will be treated confidentially. The study was a result of my curiosity to ascertain if AI-enabled sign language interpretation can resolve challenges faced by deaf students in online learning. Your response as human sign language interpreters will be useful.

Thank you.

This is a five-response format questionnaire where SA = Strongly agree, A = Agree, U = Undecided, D= Disagree and SD = Strongly disagree. Kindly tick ( ) as appropriate to you.

	Perceived benefits of AI-enabled sign language interpretation (AI-SLI)	SA	A	U	D	SD
PB1	AI-SLI can increase efficiency online education for deaf students.					
PB3	**AI-SLI** can improve lecturer-deaf students' interactions during online learning processes.					
PB4	**AI-SLI** can help solve complex sign language vocabularies.					
PB5	**AI-SLI** can lead to cost savings than using human signers.					

	Perceived benefits of AI-enabled sign language interpretation (AI-SLI)	SA	A	U	D	SD
PB6	**AI-SLI** can create new opportunities for learning in virtual classrooms.					
	Perceived Risks of AI					
PR1	**AI-SLI** may lead to expanded traumatic episodes among deaf students in virtual classrooms.					
PR2	**AI-SLI** may violate privacy concerns of teachers and students in virtual classrooms.					
PR3	Using **AI-SLI** will not be able to respond to educational needs of deaf students in virtual classrooms.					
PR4	**AI-SLI** may perpetuate bias and discrimination for deaf students in virtual classroom.					
PR5	**AI-SLI** may have unintended consequences for deaf students in virtual classroom.					
	Perceived Trust in AI					
PT2	I trust **AI-SLI** to make reliable instructional decisions.					
PT3	I believe **AI-SLI** is predictable and can be manipulated for the benefits of sign language tasks.					
PT6	I trust **AI-SLI** can supersede the efforts of human signers.					
	Cultural influence on AI-SLI					
CI1	My cultural perspective of variations in sign language influences my attitudes towards **AI-SLI**.					
CI3	**AI-SLI** development should take cultural differences into account.					
CI4	Different cultures may have different perceptions of **AI-SLI**.					
CI5	**AI-SLI** development should take cultural differences into account.					
	Future perspectives					
FP1	I believe **AI-SLI** is the future for deaf education particularly in the open distance learning programmes.					
FP2	I believe **AI-SLI** is the end of physical interaction between human sign language interpreters and deaf students.					
FP4	**AI-SLI** could eradicate empathy received by deaf people					
FP5	**AI-SLI** would enhance the individualized instruction and self-directed learning					

Demographic Information

8. **What is your age range?** (18-24, 25-34, 35-44, 45-54, 55+)
9. **Nationality…**…………………………………………………………….
10. **What is your occupation/field of study? _________________**
11. **How long have you been in your profession?__________**
12. **What is your level of education?** (High School, NCE, Bachelor's, Master's, PhD)
13. **What is your gender?** (Male, Female)
14. **Are you D/deaf or non-D/deaf**

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