Development and Validation of an Instrument Assessing Biomedical Engineering Competencies, AI Readiness, and Organisational Support

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Abstract
This study presents the development and validation of a survey instrument designed to assess the competence of biomedical engineers in AI-integrated healthcare settings. Based on the KSAA (Knowledge, Skills, Abilities, and Attitudes) framework, the instrument incorporates AI readiness and perceived organisational support (POS) as mediators of job performance. The items were adopted and adapted from established studies and refined through expert opinion analysis involving five experts from academia and industry, followed by feedback from 10 postgraduate reviewers. A pilot study was conducted with 40 biomedical engineers in this study group using the same criteria as the intended full-scale study. Data were analysed using SPSS version 30.0, focusing on internal consistency through reliability analysis. Results showed strong reliability across all dimensions, with Cronbach's alpha values ranging from 0.823 to 0.897. This paper only reports the validation phase of the instrument; testing of the mediation hypothesis will be conducted in a subsequent full-scale study. Validated instruments provide a reliable foundation for future workforce development, training programmes, curriculum enhancements, and large-scale data collection in AI-driven healthcare environments.

Keywords: AI readiness, Biomedical engineering, Competency assessment, Mediators, POS, Psychometric validation.

Introduction

In the era of digital transformation, biomedical engineers are no longer confined to ensuring the safety, functionality, and compliance of medical equipment alone. Their roles now encompass broader responsibilities, including planning, procurement, installation, maintenance, and disposal within increasingly complex and AI-driven healthcare environments (Topol, 2019; Ibrahim & Karim, 2020). These evolving functions demand not only technical expertise but also digital literacy, analytical agility, and the ability to collaborate across interdisciplinary teams (Olanrewaju & Hamid, 2021).

The emergence of smart healthcare systems underscores the need for a robust set of competencies among biomedical engineers. However, existing competency models still tend to prioritise technical knowledge over the essential cognitive, interpersonal, and attitudinal domains (Mulder 2014). The KSAA framework stands for knowledge, skills, abilities, and attitudes and offers a more holistic foundation to assess these multidimensional attributes, especially in digitally enhanced work contexts(Mahmod et al., 2025).

Importantly, the translation of individual competencies into actual workplace performance may be influenced by contextual factors such as organisational support. POS is defined as employees' perceptions of how much their organisation values their contribution and well-being, which has been linked to improved motivation, engagement, and job performance, particularly in technology adaptive roles (Eisenberger et al., 1986). Job performance, in turn, serves as a key indicator of how effectively individuals apply their competencies in practice. Complementing these relationships, AI readiness, defined as one's preparedness and confidence to work with AI systems, is gaining recognition as a critical enabler of

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performance in AI-integrated settings (Parasuraman & Colby, 2015).

Despite the significance of these constructs, there remains a lack of validated instruments that collectively examine the relationships between KSAA, POS, AI readiness, and job performance, especially within the biomedical engineering field in emerging economies like Malaysia (Olanrewaju & Hamid, 2021).

Existing engineering competency frameworks such as ABET and CDIO offer strong foundations in technical and design-orientated outcomes, particularly in areas such as problem solving, system integration, experimentation, teamwork, and design thinking. These models effectively support core engineering education and practice; however, they provide limited attention to emerging and non-technical competencies required in AI-driven work environments. Specifically, they do not adequately address digital literacy, AI readiness, behavioural adaptability, or organisational support mechanisms that influence technology adoption in modern healthcare settings. ABET's outcome criteria remain largely centred on general engineering capabilities, while CDIO highlights innovation and system integration without considering contextual enablers such as workplace culture or institutional support. To address these gaps, the present study extends these traditional frameworks by incorporating psychological and organisational constructs, namely AI readiness and POS, to better reflect the competencies needed by biomedical engineers working in AI-integrated hospitals.

Drawing from the work of van Berkum et al. (2024), who highlighted the importance of aligning graduate competencies with curriculum design in food technology education, this study adopts a similar lens within the biomedical engineering domain. It provides empirical evidence and a validated measurement instrument to support the development of competency-based curricula tailored to AI-integrated healthcare.

Therefore, this study aims to develop and validate a measurement instrument that evaluates the influence of KSAA on job performance, with AI readiness and POS modelled as dual mediators supporting educators, employers, and policymakers in aligning biomedical engineering talent with the demands of future healthcare systems.

This pilot study focuses on the development and validation of an instrument to assess competencies among biomedical engineers. The mediation effects of AI readiness and POS are not examined at this stage; these hypotheses will be tested in a subsequent full-scale study.

Conceptual Framework

This study is based on the conceptual framework (Figure 1) that integrates the knowledge, skills, abilities, and attitudes (KSAA) model with AI readiness and POS as mediating variables influencing job performance. This framework draws on well-established theories of professional competence, technology acceptance, and organisational behaviour and is adapted to the context of biomedical engineering in AI-integrated healthcare systems.

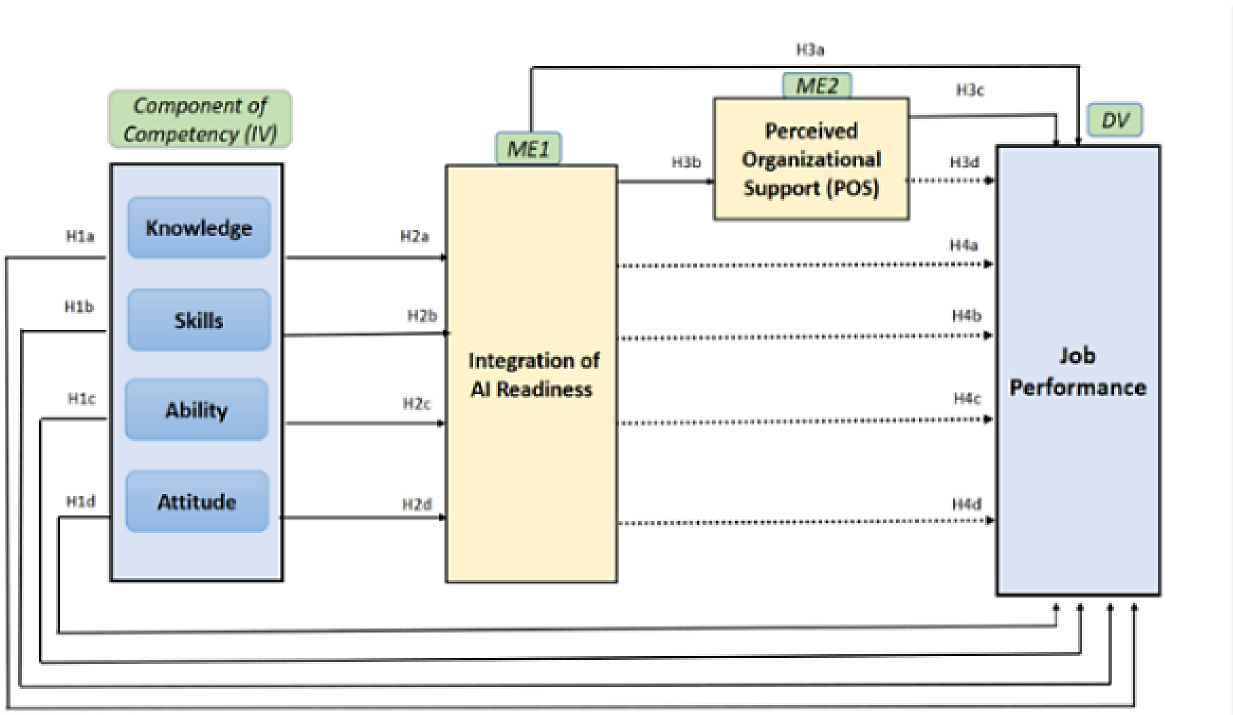

Figure 1. Conceptual framework

KSAA Competency Model

The KSAA model serves as the foundation for understanding the core attributes required by biomedical engineers to function effectively in digital healthcare environments (Mahmod et al., 2025)KSAA stands for knowledge, skills, abilities, and attitudes. It is a comprehensive framework widely used in competency modelling. Knowledge refers to the theoretical understanding of concepts, such as biomedical systems and AI applications in healthcare. Skills are the practical capabilities to apply this knowledge, including operating medical devices or interpreting AI-generated data (Mulder, 2014). Abilities encompass the cognitive and physical capacities to perform tasks, such as analytical thinking, problem-solving, and adaptability to new technologies (Spencer & Spencer, 1993). Attitudes involve behavioural and emotional dispositions that influence how tasks are approached, including motivation, responsibility, and openness to innovation (Boyatzis, 2008). Bartram (2005) explains that competence includes not just knowledge and skills but also deeper ways of thinking and attitudes that help people adapt and perform well.

AI Readiness

Malaysia offers a timely and relevant setting for this investigation. The national healthcare sector is rapidly digitalising through initiatives such as the Ministry of Health's MyDigital Healthcare Blueprint, yet structured competency models for biomedical engineers remain underdeveloped. Existing research, including Olanrewaju and Hamid (2021), has highlighted persistent digital-skills gaps and uneven AI adoption across public and private hospitals. Moreover, current professional and institutional frameworks in Malaysia have not fully integrated AI readiness as a core competency requirement. Validating an AI-related competency instrument within this context directly addresses a pressing workforce and educational need while also generating insights that may be transferable to other emerging economies undergoing similar transitions.

AI readiness refers to an individual's preparedness, willingness, and confidence to work with artificial intelligence tools and systems (Parasuraman & Colby, 2015). It encompasses digital literacy, technological optimism, and perceived self-efficacy in using AI. In engineering environments, AI readiness functions as a psychological enabler that influences how effectively individuals can apply their competencies in AI-driven settings. Accordingly, it is positioned as a mediator between KSAA and job performance, reflecting its role in translating core attributes into technology-enhanced outcomes (Marques & Ferreira, 2020). In the Malaysian healthcare context, where AI implementation is accelerating but workforce preparedness remains inconsistent, this construct is particularly significant for understanding competency gaps and informing targeted capacity building.

Perceived Organisational Support (POS)

POS is conceptualised as the extent to which employees believe that their organisation values their contributions and supports their professional development (Eisenberger et al., 1986). In the context of technological change, POS enhances individual motivation, reduces uncertainty, and facilitates continuous learning. This study hypothesises that POS mediates the relationship between KSAA and job performance by providing an enabling organisational environment that fosters skill application and professional growth (Chow et al. 2018). It complements AI readiness by addressing the social and structural aspects of technology adoption.

Job Performance

Job performance is treated as the outcome of the conceptual model and includes both task-based and adaptive dimensions. Drawing from Campbell & Wiernik (2015), performance in dynamic environments such as AI-integrated healthcare involves not only technical execution but also innovation, continuous learning and responsiveness to digital transformation. Biomedical engineers' job performance is thus influenced by both internal (KSAA) and external (AI readiness and POS) factors.

Method

This study was conducted in five sequential stages to develop and validate a competency measurement instrument for biomedical engineers in AI-integrated healthcare settings.

In Stage 1, the questionnaire was designed based on the objectives of the study, using the method of adaptation and adoption from previous validated instruments related to knowledge, skills, abilities, and attitudes (KSAA), AI readiness, POS, and job performance (Boyatzis, 2008; Hung et al., 2020).

In Stage 2, the Expert Opinion Analysis (EOA) instrument was reviewed by a panel of five subject matter experts, comprising academic professionals and industry practitioners, to evaluate the content, clarity, and relevance of each item.

Next, in Stage 3, the refined questionnaire underwent a validation process and was submitted for ethical review and approval by the Universiti Teknologi Malaysia (UTM) ethics committee to ensure adherence to research integrity and ethical guidelines (Universiti Teknologi Malaysia, 2022).

Following this, in Stage 4, a user feedback session was conducted with 10 postgraduate students who reviewed the instrument to establish face validity and provided feedback regarding the clarity and comprehensibility of the items (DeVellis, 2017).

Finally, in Stage 5, a pilot study was conducted with 40 biomedical engineers who fulfilled the sampling criteria. The pilot data were analysed using SPSS Version 30.0, where Cronbach's Alpha (CA) was used to assess the internal consistency and reliability of each construct. According to Song (2020), the CA coefficient is appropriate for determining the homogeneity of Likert-scale items. Additionally, descriptive statistics were used to analyse Section A, which comprised the demographic profile of the respondents.

This study employed a quantitative pilot approach with an embedded validation framework for instrument development. The validation process was conducted in several structured phases to ensure both content and construct validity prior to full-scale deployment. Instrument Development and Validation Process:

The development of the survey instrument followed a five-phase process:

Stage 1: Item Construction

The development of the survey instrument began with the item construction phase, guided by a comprehensive review of relevant literature and supported by well-established theoretical frameworks, namely the KSAA competency model (Boyatzis, 2008; Mulder, 2014), the Technology Readiness Index for AI readiness (Parasuraman & Colby, 2015), Social Exchange Theory underpinning Perceived Organisational Support (Eisenberger et al., 1986), and the performance model by Campbell et al. (1993) for job performance. The instrument was designed to investigate the relationship between the key variables in this study: KSAA the independent variable, job performance as the dependent variable, and AI readiness, along with POS as dual mediators (Boyatzis, 2008; Campbell et al., 1993; Hung et al., 2020). This theoretical foundation reflects the critical competencies and organisational support factors required for biomedical engineers to perform effectively in AI-integrated healthcare environments. An initial pool of items was developed by adapting and adopting validated measures from prior studies to ensure conceptual clarity and content relevance (DeVellis, 2017).

The survey instrument was structured into five main sections as follows:

i. Section A: Demographic Information is collecting background data on respondents, including age, gender, years of professional experience, and highest level of education (Fink, 2017).
ii. Section B: Competency Components (KSAA) assesses respondents' knowledge, skills, abilities, and attitudes related to biomedical engineering in digital healthcare settings (Boyatzis, 2008; Mulder, 2014).
iii. Section C1: AI Readiness is measuring the extent of respondents' preparedness and confidence in working with AI technologies (Parasuraman 2015).
iv. Section C2: POS and evaluating the level of support respondents perceive from their organisations in adopting AI-related tasks (Eisenberger 1986).
v. Section D: Job Performance is capturing self-reported measures of effectiveness and work outcomes in AI-integrated tasks (Koopmans 2013).

All items in Sections B through D were measured using a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree", adopted from Song (2020). This structured instrument served as the foundation for subsequent expert validation and psychometric testing.

Stage 2: Expert Opinion Analysis (Content Validity)

To ensure content validity, the draft instrument was assessed by a panel of five subject matter experts, consisting of academic experts in biomedical engineering, artificial intelligence, competency, and job performance, and industry professionals with experience in the healthcare technology sector. These experts were selected for their domain knowledge and practical insights relevant to the study context. The assessment focused on key aspects such as item relevance, wording clarity, and subject matter expertise. Each expert provided qualitative ratings and comments. Quantitative assessment was conducted using the Content Validity Index (CVI), allowing for a structured assessment of the appropriateness of each item (Zamanzadeh et al., 2015). Based on the CVI scores and expert feedback, several items were revised, refined, or removed to improve the conceptual accuracy and linguistic clarity of the instrument before moving on to the next validation phase.

Stage 3: Ethical Review

In the third stage, the refined version of the questionnaire underwent a formal validation and ethical review process. This involved ensuring that the instrument met the necessary standards for research quality, participant protection, and data confidentiality. The complete set of questionnaire items is finalised after expert review is submitted to the Universiti Teknologi Malaysia (UTM) Research Ethics Committee. The purpose of this submission was to obtain ethical clearance in accordance with institutional protocols and national research ethics guidelines (Universiti Teknologi Malaysia, 2022). Therefore, the researcher obtained confirmation from UTM Ethics Approval on July 30, 2025, Bill 8/2025. Approval number: UTMREC-2025-160 verbal and written feedback. The approval process ensured that the study adhered to principles of research integrity, including informed consent, voluntary participation, and the ethical handling of participant data. Only after receiving official ethical approval was the study allowed to proceed to the next phase of data collection.

Stage 4: User Review (Face Validity)

To ensure clarity, readability, and practical interpretability of the survey instrument, the revised questionnaire was reviewed by 10 postgraduate students who represented the target population. Their feedback focused on the wording, item sequencing, and overall usability of the instrument. Based on their input, necessary adjustments were made to improve the phrasing and flow of the questionnaire. This process helped establish face validity, ensuring that the instrument was understandable and appropriate for use in the actual data collection phase (DeVellis, 2017).

Stage 5: Pilot Study (Construct Validation)

The finalised version of the survey instrument was pilot-tested with a sample of 40 biomedical engineers working in private hospitals across Malaysia. These participants were purposefully selected to reflect characteristics similar to the intended study population, ensuring contextual relevance to AI-integrated healthcare environments. A sample size of 30 to 50 participants is generally considered adequate for pilot testing of survey instruments, as recommended by Johanson and Brooks (2010), who state that a minimum of 30 respondents is sufficient to identify preliminary validity and reliability issues. Similarly, Hertzog (2008) supports the use of 10–40 participants for pilot studies aimed at refining instruments and assessing feasibility.

The primary objective of the pilot study was to evaluate the instrument's construct validity and internal consistency prior to its full-scale administration (DeVellis, 2017; Boateng et al., 2018). During this phase, the researchers examined the dimensional structure of the instrument and assessed whether the items were interpreted consistently and meaningfully by respondents. The pilot also helped detect any issues related to item clarity, response bias, or scale performance (Netemeyer et al., 2003).

To assess reliability, Cronbach's Alpha values were used as the benchmark. According to Hair et al. (2020), values above 0.70 indicate acceptable reliability, values between 0.80 and 0.90 reflect very good internal consistency, while values above 0.90 may suggest redundancy. Since all constructs in this study exceeded the acceptable threshold, a repeated measure such as test–retest was not deemed necessary at the pilot stage.

The results of the pilot study provided the empirical foundation to confirm the psychometric robustness of the instrument, ensuring it was suitable for broader data collection and further statistical analysis.

Data Analysis

The data analysis in this study involved two key approaches: psychometric evaluation and preliminary conceptual modelling. Several statistical methods were employed to assess the quality of the instrument and to explore the relationships between study constructs, including descriptive statistics and reliability analysis (DeVellis, 2017).

Firstly, descriptive statistics were used to analyse Section A of the questionnaire, which captured respondents' demographic information. This section consisted of four key elements: age, gender, working experience and education level. This analysis provided an overview of the respondent profile and ensured that the sample was representative of the target population.

Next, to assess internal consistency, Cronbach's alpha coefficients were calculated for each construct. The results indicated high reliability, with all constructs achieving alpha values above 0.80, which is considered very good according to Hair et al. (2020). This confirmed that the items within each construct consistently measured the intended dimension.

The interpretation scale for Cronbach's Alpha used in this study is shown in Table 1.

Table 1. Scale for Cronbach's Alpha

Alpha Coefficient Range	Strength of Association
< 0.6	Poor
0.6 to < 0.7	Moderate
0.7 to < 0.8	Good
0.8 to < 0.9	Very Good
0.9	Excellent

Source: (Hair *et al.*, 2020)

Results

These results are from the findings of the pilot study conducted among 40 biomedical engineers in the group of the study. The results encompass demographic profiles, descriptive statistics of key constructs, and internal consistency reliability testing for the developed instrument.

Respondent Demographics

The sample consisted of 40 biomedical engineers from both public and private hospitals (Table 2). The gender distribution was relatively balanced, with 21 female respondents (52.5%) and 19 male respondents (47.5%). In terms of age, the majority were between 31 and 40 years old (62.5%), followed by those aged 22–30 years (22.5%) and 41–50 years (15%).

Table 2. Gender Demographics

Category	Count	Percentage
Male	19	47.5
Female	21	52.5
	40	100%

Descriptive Statistics

The pilot study findings revealed consistently high mean values across all seven measured constructs are knowledge, skills, ability, and attitude (KSAA), AI Readiness, POS, and Job Performance are accompanied by relatively low standard deviations. This suggests a high degree of response consistency and a generally positive perception among participants regarding the measured domains.

Specifically, the core KSAA components recorded mean scores ranging from 21.18 to 21.90 on a 25-point scale. AI Readiness recorded a mean of 57.72 (SD = 8.34), POS recorded a mean of 42.45 (SD = 6.89), and Job Performance scored a mean of 68.40 (SD = 8.41). These results indicate that the instrument is well-understood, contextually appropriate, and capable of capturing the key constructs relevant to biomedical engineers in AI-integrated healthcare environments.

Overall, the pilot phase supports the instrument's suitability for full-scale deployment in the next phase of the study.

Reliability Analysis

To assess internal consistency reliability, Cronbach's Alpha coefficients were computed for each construct. All seven constructs exceeded the acceptable threshold of 0.80, indicating strong internal reliability and coherence among items. The highest reliability was recorded for the Attitude dimension (α = 0.897), followed by Knowledge (α = 0.884) and POS (α = 0.877). These results affirm the stability and consistency of the instrument's measurement properties across constructs.

The summary of reliability results is presented in Table 3 below.

Table 3. Reliability Statistics of Constructs (n = 40)

Construct	No. of Items	Cronbach's Alpha	Mean	Std Dev.
Knowledge	5	0.884	21.70	2.38
Skills	5	0.854	21.33	2.44
Ability	5	0.823	21.18	2.35
Attitude	5	0.897	21.90	2.52
AI Readiness	16	0.854	57.72	8.34
POS	12	0.877	42.45	6.89
Job Performance	18	0.853	68.40	8.41

(Source: Author)

Comparison with Previous Studies

The reliability coefficients obtained in this pilot study align well with prior research that has examined similar constructs within the domains of engineering competencies, AI readiness, and POS. The KSAA domains, the Cronbach's Alpha values ranging from 0.823 to 0.897 are consistent with findings by Mulder (2014) and Bartram (2005), who emphasised the robustness of multi-domain competency models in professional settings. In the engineering education context, van Berkum et al. (2024) reported Cronbach's Alpha values between 0.82 and 0.89 across cognitive, interpersonal, and technical clusters in a competency validation study for food technology graduates, supporting the structural integrity of similar constructs.

Regarding AI readiness, the internal consistency of 0.854 matches values observed in recent adaptations of the Technology Readiness Index (TRI 2.0) and AI for specific instruments. For instance, Parasuraman & Colby (2015) reported alpha values between 0.83 and 0.87 for constructs such as optimism and innovativeness in AI adoption. Similarly, Marques & Ferreira (2020), who measured digital readiness in STEM professionals, documented an internal consistency of 0.85–0.88, reinforcing the reliability of digital and AI readiness dimensions in technical environments. Meanwhile, for POS, the result of 0.877 is within the range of prior studies. According to Eisenberger et al. (2002), they originally reported alpha values above 0.80 in their POS scale development. More recent studies in healthcare and engineering domains, such as Chow et al. (2018), also observed reliability coefficients between 0.83 and 0.89, confirming the stability of POS as a mediating variable influencing job performance and learning engagement.

The Job Performance construct, with a reliability of 0.853, is similarly supported by research in engineering and healthcare workforce evaluations. Campbell & Wiernik (2015) identified consistent reliability levels when job performance was assessed through multi-dimensional behavioural indicators. In sum, the internal consistency reliability demonstrated in this pilot study is in strong agreement with earlier validated scales, confirming the suitability of the instrument for subsequent empirical studies in biomedical engineering and AI-integrated workplace settings.

Discussion

The findings of this pilot study provide empirical support for the reliability and preliminary construct validity of the developed instrument to assess biomedical engineering competencies and AI readiness. The strong internal consistency across all constructs indicates that the questionnaire items are coherent, relevant, and well-understood by professionals working in AI-integrated healthcare environments. These results offer important insights into the preparedness of biomedical engineers for evolving technological demands, with implications for curriculum development, workforce training, and policy planning.

Firstly, the consistently high reliability coefficients for the KSAA constructs knowledge (α = 0.884), skills (α = 0.854), ability (α = 0.823), and attitude (α = 0.897) demonstrate that the instrument effectively captures the multidimensional nature of professional competence. This aligns with well-established competency frameworks in engineering and education literature, such as those proposed by Bartram (2005) and Mulder (2014), which emphasise the integration of technical, cognitive, and attitudinal domains. The inclusion of attitudinal elements is particularly relevant in AI-driven contexts, where adaptability, openness to innovation, and digital confidence are increasingly recognised as enablers of performance.

Secondly, the reliability of the AI Readiness construct (α = 0.854) reflects growing awareness among biomedical engineers of the need to engage with AI-enabled systems. This aligns with previous research by Parasuraman and Colby (2015) and Marques and Ferreira (2020), which frame readiness as a cognitive-emotional state that influences effective technology use. The high reliability score in this study suggests that the instrument is appropriately designed and easily interpreted for subsequent large-scale use.

Thirdly, the findings reinforce the importance of POS, which recorded a Cronbach's alpha of 0.877. This highlights POS as a critical mediating factor shaping engineers' confidence, performance, and retention, particularly in sectors experiencing technological transition. Consistent with Eisenberger et al. (2002), organisational investment in employee development and digital upskilling is essential in high-technology environments such as biomedical engineering.

The Job Performance construct also demonstrated strong reliability (α = 0.853), validating the behavioural indicators used in the instrument. The inclusion of both technical execution and adaptability to AI-enhanced settings allows for a comprehensive assessment of engineering outcomes. This dual focus supports data-driven improvements in curriculum design, performance appraisal, and professional accreditation.

Although this pilot was conducted among biomedical engineers in Malaysia, the theoretical constructs underpinning the instrument KSAA, AI readiness, and POS are globally relevant. Overall, the validated instrument demonstrates strong potential to inform empirical research, curriculum enhancement and policy development in biomedical engineering education and workforce planning. Its ability to capture competencies, contextual enablers, and performance outcomes positions it as a timely contribution to AI-integrated healthcare practice.

Limitations of the Study

This pilot study has several limitations. The sample was small and drawn exclusively from private hospitals in Malaysia; thus, the findings cannot be generalised to biomedical engineers in public healthcare institutions or other countries. Nevertheless, the Malaysian context is a relevant setting to explore this gap, as it represents a developing healthcare system progressively integrating artificial intelligence into biomedical engineering practice. The reliance on self-reported data also introduces the risk of social desirability bias, where participants may overstate their competencies or readiness levels. Future studies should incorporate supervisor ratings, peer evaluations, or objective performance indicators to mitigate such bias. A larger and more diverse sample, combined with triangulated data sources, would strengthen the robustness, reliability, and generalisability of future research outcomes.

Conclusion

This pilot study has successfully developed and validated a multidimensional measurement instrument that evaluates biomedical engineering competencies, AI readiness, POS, and job performance. The findings demonstrate strong internal consistency across all constructs, confirming the reliability of the instrument for use in AI-integrated healthcare environments. The high mean scores across KSAA domains suggest that biomedical engineers in Malaysia perceive themselves as well-equipped with core competencies, particularly in technical, cognitive, and attitudinal areas. Furthermore, the strong reliability of the AI readiness and POS constructs reinforces their relevance as mediating variables that influence how individual attributes translate into actual job performance.

From an educational perspective, this instrument provides a valuable tool for curriculum designers, educators, and policymakers to assess and align graduate competencies with industry needs. The inclusion of AI readiness and POS offers a novel contribution to engineering education by accounting for both individual preparedness and contextual enablers. This supports the broader shift toward competency-based education and digital transformation in STEM fields. The validated instrument may now be deployed in a full-scale study to examine the mediating effects of AI readiness and POS on the relationship between KSAA and job performance. Such research can inform national talent development strategies and workforce planning in the biomedical engineering sector.

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Conflict of Interest Statement

The author declares that there is no conflict of interest associated with the conduct of this research or the preparation of this manuscript.

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