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A Data-Driven Needs Analysis of the E-SIS Competency System for Integrating AI into POLYCC-TVET Talent Management

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ABSTRACT

Implementing Artificial Intelligence (AI) in talent management systems has become an urgent force behind enhancing the workforce capacity, especially in the Jabatan Pendidikan Politeknik dan Kolej Komuniti - Technical and Vocational Education and Training (POLYCC-TVET) ecosystems that are being digitalized. This paper provides a quantitative needs analysis of the e-SIS competency system in order to assess the system's being ready, needing, and able to integrate AI into assisting with talent analytics among POLYCC-TVET educators. The study used a quantitative survey design to analyse seven (7) important constructs, which include system efficiency, data and infrastructure preparedness, competency analytics capability, support of leadership development, acceptance of AI/ML integration, individual literacy and technical skills, and perceived effect of AI-enabled talent management (used 144 lecturers and training officers in polytechnics and community colleges). Empirical strength was ensured with the use of descriptive analytics, competency gap analysis and reliability testing (Cronbach's Alpha=0.898-0.973). The results show that the general level of agreement is 85.3%, which means that institutions are highly prepared to start adopting AI. The highest were the system efficiency (95.3%), AI acceptance (98.2%), and the perceived AI impact (95.2%) as it reflects trust in the system's possibility to improve the precision of competency evaluation and information-driven decision-making. Nevertheless, gaps were found in standardised competency taxonomies, API interoperability, and personal technical literacy and particularly scripting and model interpretation (62.2%). These points indicate the necessity of well-organized AI capacity-building programmes, better data governance and system interoperability to use AI-enabled competency analytics to their full capacity. This research gives a substantial evidence-based foundation to the creation of an AI-based POLYCC-TVET talent management model and offers policymakers, system developers and institutional leaders information on how to modernise talent governance in national TVET systems.

Keywords: Artificial Intelligence; POLYCC-TVET; Talent Management; Competency Analytics; Competency Systems.

INTRODUCTION

The economic trend of moving towards skills-based economies worldwide emphasizes the significance of Technical and Vocational Education and Training (TVET) institutions in establishing effective talent management systems in the effort to make the workforce employable and the educators maintain their competency levels through constant improvement. The recent *Dasar TVET Negara 2030* highlights data-driven change and digital preparedness of TVET providers as one of the strategies to deliver high-skilled talent in accordance with the national workforce needs in Malaysia (Sekretariat Majlis TVET Negara, 2024). In educational contexts, artificial intelligence (AI) has already shown significant potential to automate the administrative processes, to customize the learning processes, and to improve the accuracy of skills and competencies assessments and make AI a key tool to modernize the talent and competency management systems (Bond et al., 2024). The results of systematic reviews of AI in education indicate that AI is increasingly becoming a part of instructional practices, assessment, and administrative processes, which supports the argument of incorporating AI in education management systems (Almasri, 2024).

Simultaneously, the introduction of AI into human resource management and talent potential evaluation has also been growing faster; the application tools based on AI assist in skill-to-job mapping, competency analysis, training recommendations and predictive analytics to forecast performance capabilities that are essential to a data-driven talent management model (Wang et al., 2024). Along with these possibilities, successful implementation of AI requires well-developed data infrastructure, compatibility of systems, common competence taxonomies, and adequate technical literacy of users (Chee et al. 2025). The preliminary needs analysis of the current e-SIS competency system within the framework of the TVET Applied Research Grant Scheme (T-ARGS) Project demonstrates that the institutional support and perceived willingness to adopt AI are high, yet it also shows that a considerable number of gaps in data standardization, API integration, and individual technical capabilities required to implement artificial intelligence/machine learning (AI/ML) modules need to be addressed.

Considering such opportunities and limitations, this research presents a data-driven needs analysis of the e-SIS competency system to determine the priority areas where the system should be developed, trainer requirements and technical specifications needed to support AI-enabled competency analytics and talent management at POLYCC-TVET institutions. The findings are expected to offer empirical data that will help guide system developers, policymakers, and institutional stakeholders in the planning of coordinated AI-based talent management solutions to support national TVET transformation objectives.

LITERITURE REVIEW

The past few years have seen more integration of artificial intelligence (AI) in education, not just in primary and secondary education but also in technical and vocational education and training (TVET) as part of a wider initiative to move the workforce towards workforce digital readiness. By relying on the systematic review by Rosyadi et al. (2023), it was evident that AI application in TVET contexts (2018-2023) has a transformative potential: efficiency, customized learning paths, assessment, and institutional effectiveness (Rosyadi et al., 2023). On the same note, general observers in AI in education indicate that AI-based solutions positively impact the instruction, evaluation and management in all education levels that provide predictive analytics, automated feedback, and data-driven decision support (Mallik and Gangopadhyay, 2023).

On the same level with these developments is the continuing demand to place TVET systems in line with Industry 4.0 requirements. Recent systematic literature by Rajamanickam et al (2024), reminds of the need to incorporate technologies such as AI, big data, IoT and robotics in TVET curricula and institutional frameworks to graduate students who would find employment in digital-era workplaces (Rajamanickam et al. 2024). The review lists the gains that include more relevant training, better match with labour market needs, and increased flexibility as well as two (2) constraints such as unequal access to resource, infrastructure disparity, and heterogeneity of institutions towards the adoption of advanced technologies.

More precisely, several empirical research works discuss the use of artificial intelligence in assessment and competency evaluation in the context of TVET. As an example, research by Onatere-Ubrurhe and Ubrurhe (2025) investigates the initiation of an AI-based assessment mechanism to mitigate the weaknesses of traditional systems in assessing 21st-century skills such as creativity, problem-solving, and innovation dimensions (Onatere-Ubrurhe & Ubrurhe, 2025). Another article by Noor et al. 2025, suggests a model of AI-powered personalized learning in TVET institutions, noting that adaptive learning systems that are consistent with institutional enterprise architecture have the potential to promote learner-centered instruction, development of skills, and workforce preparedness (Noor et al., 2025).

In addition to technical and pedagogical changes, the readiness of institutions and teachers to introduce AI is a common theme. The article by Amalina et al. 2025, was written in a recent Malaysian context and explores the institutional readiness to adopt AI. The research highlights various dimensions, organization culture, the role of leadership, infrastructure, knowledge management, and security. Results indicate that such barriers as resource constraints, low digital literacy, and absence of strategic planning vary in the readiness of staff and management (Amalina et al. 2025).

Simultaneously, studies examining the trends in digital competence in vocational education by Rahmawati et al. 2025 indicate that digital competence, including AI-readiness, is becoming the center of attention of educators and learners in TVET. Their bibliometric survey (216 articles) demonstrates that even though AI literacy is increasingly being incorporated into the available digital competence models, its implementation remains insufficient and requires more elaborate models that integrate digital skills, social competencies, and AI readiness (Rahmawati et al. 2025).

Finally, the most recent meta-views of AI in education call upon treating it with caution and focusing on human-centred design alongside ethical, privacy, and trustworthiness concerns. The article by Alfredo et al. 2025 observes that although AI-enabled learning analytics may be scalable and data-driven, many of them lack proper stakeholder engagement transparency and safety controls that could undermine user trust and the ultimate adoption (Alfredo et al., 2024).

METHODOLOGY

This study employed a quantitative survey design to conduct a data-driven needs analysis of the e-SIS competency system for integrating artificial intelligence (AI) into POLYCC-TVET talent management. The desired direction was a quantitative method that will help quantify the prevalence and magnitude of readiness, acceptance, and competency gaps across the defined constructs as well as to present empirical evidence that is appropriate to inform system requirements and policy decisions (Wang et al., 2024). The developed survey instrument was based on the requirement analysis framework and literature about AI readiness and competency analytics and consisted of seven constructs, namely system efficiency, data and infrastructure readiness, competency analytics capacity, leadership development capacity, AI/ML acceptance, individual literacy and technical skills, and perceived impact/value of AI/ML. Based on the needs analysis, item statements were translated into statements based on the result with an 8-point Likert scale to enhance sensitivity and lessen the bias of central tendency. The main tool and construct operationalisation is also presented in the result and formed the basis of the empirical measures of this study.

TVET trainers and training officers in Malaysian polytechnics and community colleges (POLYCC) were the members of the study population that would be the key consumers of e-SIS. A convenience sampling strategy was used to the extent that practitioners that were available by the means of institutional networks were reached, which resulted in N = 144 valid responses and is similar to the initial dataset. Participants had to meet the inclusion criteria that included being a current member of POLYCC-TVET staff and taking an active part in competency tracking or staff development practice. The choice of the sample size was also based on the advice on survey-based research in educational technology and organisational research, where a sample size of above 100 is considered to render sufficient statistical power when conducting descriptive and reliability analyses in instrument development research (Chen et al. 2020).

The online questionnaire (Google Forms) was implemented to collect data through institutional mailing. Online modality allowed reaching a wider geographic range and effective aggregation of responses with anonymity (Uygun, 2024). In order to achieve content validity, the three (3) domain experts (POLYCC-TVET administrators, AI in education researchers, and HR analytics practitioners) revised the instrument and piloted it on a sample of practitioners (n = 20) to test the clarity of the items and the response patterns (Sallam et al. 2023). The pilot feedback was used to make slight changes in wording, and the final survey was finally launched to collect all data. This is consistent with modern advice on the creation of instruments and pilot testing of educational questionnaires (Miao & Zhang, 2025).

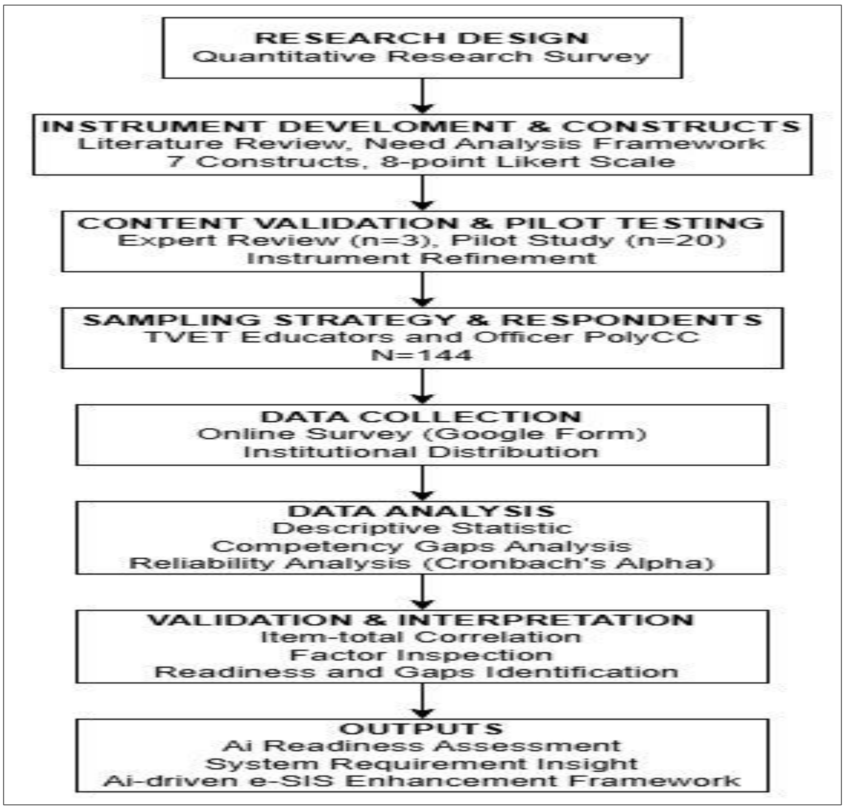

Figure 1: Research Methodology Design

Descriptive statistics were integrated with analytical procedures and competency gap analysis and reliability testing (Mujahid et al., 2024). The descriptive statistics (means, standard deviations, frequencies) summarised the demographics and construct scores to define the levels of readiness and areas of high/low scores (Punzalan et al., 2025). It was a competency gap analysis that contrasted the level of observed competencies with the expected proficiency to identify the features of the system to prioritize and training requirements (Sütőová et al., 2025). The internal consistency reliability was evaluated by using Cronbach alpha on each of the constructs, which is the standard practice in psychometric testing; the outcome reports alpha coefficients of between 0.898 to 0.973 which implies that the constructs used in this study have high internal consistency (Ahmad et al., 2024). Additional tests like item-total correlations and exploratory factor inspection were done to verify the coherence in the construct and to identify any troublesome items that might question the validity of the scale. However, the methodological design that incorporates validated survey constructs, reliability testing, pilot validation, and corroborative system document review will offer a strong empirical foundation to formulate AI integration priorities and design specifications of the e-SIS competency platform.

RESULTS

The finding of the data-driven needs analysis based on the data demonstrates that generally, POLYCC-TVET educators and institutions are highly prepared to adopt AI in the e-SIS competency ecosystem. Based on 144 respondents (polytechnics, community colleges, and JPPKK), the survey demonstrates an overall level of agreement of 85.3% which means that there is general support towards improving the process of talent management in relation to the use of AI-enabled analytics and recommendation systems. The demographics of the respondents show that most of them are long-term which is over 10 years an experienced educators in polytechnics and community college, therefore, most of them have some form of preliminary exposure to AI/ML concepts, which in turn serves to confirm the possibility of future adoption of the system with AI improvements.

System Efficiency

The e-SIS platform has been found to be very efficient based on the mean agreement level of 95.3%, the largest among all constructs as shown in Table 1. According to the respondents, the system accessibility (Mean=6.65, SD=1.061), data accuracy (Mean=6.55, SD=1.076), and the ease of generating reports (Mean=6.41, SD=1.179) are highly satisfied. Such items as e-SIS can be easily accessed and are user-friendly and data presented in e-SIS is up-to-date and have mean scores that are higher than 6.5 on an 8-point scale. These findings reiterating the significance of the usability of digital systems as a requirement to introduce AI into the system and its possible positive impact on the efficiency of the work of educators go in line with the changing role of technology in the educational process. Nevertheless, the scores obtained slightly lower on the completeness of integrated data indicate that better interoperability and aggregation features are required.

Table 1: e-SIS System Efficiency

Item	Section B: e-SIS System Efficiency	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
B1	The e-SIS system is easily accessible and user-friendly.	3.5	96.5	1.061	6.65	7	7
B2	The information search process in the e-SIS system is fast.	4.9	95.2	1.215	6.42	7	7
B3	The data displayed in the e-SIS system is up to date.	2.8	97.2	1.059	6.61	7	7
B4	Lecturer competency data in the e-SIS system is accurate.	2.1	97.9	1.076	6.55	7	7
B5	Reports can be easily generated from the e-SIS system.	7.0	93.0	1.179	6.41	6	6
B6	The e-SIS system provides complete information without the need for additional manual searches.	7.7	92.4	1.193	6.33	6	6
	Average %	**4.7**	**95.3**				

Data and Infrastructure Readiness

The second key construct has more moderate levels of readiness at 89.0% as shown in Table 2, although considerable gaps exist regarding metadata standards (Mean=5.96, SD=1.228), capacity in terms of API integration (Mean=5.65, SD=1.465), and the sufficiency of the infrastructure to use AI (Mean=6.09, SD=1.176). Objects associated with interoperability (e.g., integration with HRMIS, SPMP, CIDOS) are the objects of the lowest mean values (5.65-5.96), which means that it is critical to modernise data systems at the back end before integrating AI analytics. These results indicate that interoperability and data governance are crucial preconditions to AI-driven education systems.

Table 2: Data and Infrastructure Readiness

Item	Section C: Data and Infrastructure Readiness	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
C1	PPPT competency and training data is stored with a clear structure.	4.9	95.1	1.147	6.49	7	7

C2	The data quality (complete, accurate, consistent) of the e-SIS system is sufficient to implement AI models.	7.0	93.1	1.190	6.24	6	7
C3	Data access is granted in accordance with role-based access.	3.5	96.5	1.122	6.51	7	7
C4	Existing e-SIS systems support API/interop integration (HRMIS, SPMP, CCMS, CIDOS etc.)	22.3	77.8	1.465	5.65	6	6
C5	There is a standard PPPT competency taxonomy for e-SIS system user guidance.	13.2	86.8	1.372	5.88	6	6
C6	Metadata & audit logs are stored for traceability.	13.2	86.8	1.228	5.96	6	6
C7	I believe the infrastructure (GPU/computation/cloud) is sufficient for the implementation of the AI project of the e-SIS system.	9.7	90.2	1.176	6.09	6	6
C8	Budget allocations/analytical software licenses are provided on an ongoing basis for the sustainability of e-SIS system management.	14.6	85.5	1.369	6.01	6	6
	Average %	**11.0**	**89.0**				

Competency Analytics Capability

The capability of e-SIS to support competency analytics is rated moderately high (80.2% agreement) as shown in Table 3. According to respondents, the system could be used to identify gaps in competency (Mean=5.62, SD=1.447) and facilitate training planning (Mean=5.80, SD=1.585), but they also identify limitations in automated recommendations as an area where AI recommender systems could provide considerable value. The comparatively low mean score of the system suggests relevant training based on competency gaps (Mean=5.58, SD=1.628) highlights a functional impairment that could be overcome by AI-driven analytics. These results assist with personalised competency development contexts and AI-enabled adaptive training in POLYCC-TVET surroundings.

Table 3: Competency Analytics Capability

Item	Section D: Competency Analytics Capability	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
D1	The e-SIS system can accurately identify lecturer competency gaps.	21.6	78.5	1.477	5.62	6	6
D2	The e-SIS system can match lecturer competencies with industry needs.	16.0	84.0	1.418	5.67	6	6
D3	The e-SIS system suggests relevant training based on competency gaps.	23.0	77.1	1.628	5.58	6	6

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D4	The e-SIS system monitors competency development after training.	18.8	81.2	1.55	5.77	6	6
D5	The e-SIS system helps plan training and staff development strategically.	19.5	80.5	1.585	5.80	6	7
	Average %	**19.8**	**80.2**				

Leadership Development Capability

The preparation for AI-assisted leadership development also has high agreement (82.2%) as shown in Table 4. The system is considered to be able to track leadership KPIs (Mean=5.9, SD=1.469) and facilitate succession planning (Mean=5.76, SD=1.529), though users are explicitly concerned that it is not accurate at identifying high-potential leaders (Mean=5.47, SD=1.621). These views support the results of the AI-based talent identification study, which states that when competency and behavioural data sets are strong, machine-learning models can increase the level of accuracy of leadership prediction.

Table 4: Leadership Development Capability

Item	Section E: Leadership Development Capability	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
E1	The e-SIS system can identify lecturers with potential to become leaders.	24.4	75.7	1.621	5.47	5.5	5
E2	The e-SIS system supports succession planning.	18.1	81.9	1.529	5.76	6	7
E3	The e-SIS system provides recommendations for appropriate leadership development interventions.	19.5	80.5	1.491	5.67	6	7
E4	The e-SIS system helps monitor the progress of leadership program participants.	16.7	83.3	1.505	5.79	6	6
E5	The e-SIS system automatically tracks leadership development KPIs (e.g. training hours, mentors, impact projects).	15.3	84.6	1.469	5.90	6	7
E6	A readiness report for replacement candidates can be generated when needed.	17.4	82.7	1.441	5.69	6	7
E7	360-degree assessment data (MyDHProfile360) can be integrated to support leadership development decisions.	15.3	84.7	1.429	5.74	6	6
E8	The e-SIS system can recommend suitable mentors/coaches based on your profile and development objectives.	16.0	84.0	1.466	5.72	6	6
	Average %	**17.8**	**82.2**				

AI/ML Acceptance

The strongest construct of all is the acceptance of artificial intelligence (AI) and machine learning (ML), and the agreement level is impressive (98.2%) as presented in Table 5. The respondents strongly agree that AI will

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enhance competency analysis (Mean=6.55, SD=1.023), training recommendations (Mean=6.57, SD=1.001), leadership identification (Mean=6.52, SD=1.017) and general user experience (Mean=6.58, SD=0.964). These high levels of acceptance mean that the educationists are slowly becoming convinced of AI systems when they see that there are tangible benefits and low complexity of use. This cultural and psychological preparedness is high placing the POLYCC-TVET institutions in a positive position to adopt AI.

Table 5: AI/ML Acceptance

Item	Section F: AI/ML Acceptance (e-SIS Improvement)	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
F1	I believe the integration of AI/ML in the e-SIS system can improve the accuracy of competency analysis.	2.1	97.9	1.023	6.55	7	7
F2	I believe the integration of AI/ML in the e-SIS system can help the system recommend training more accurately.	1.4	98.6	1.001	6.57	7	7
F3	I believe the integration of AI/ML in the e-SIS system can better identify leadership potential.	2.8	97.2	1.017	6.53	7	7
F4	I believe the experience of using the e-SIS system will be better with AI/ML integration.	1.4	98.6	0.964	6.58	7	6
F5	I am interested in using the AI/ML-equipped e-SIS system, if developed.	1.4	98.6	1.019	6.69	7	7
	Average %	**1.82**	**98.2**				

Individual Literacy and Technical Skills

On the contrary, the lowest scores are produced in individual literacy and technical skills with 62.2% agreement as shown in Table 6. Although the respondents are knowledgeable about AI concepts (Mean=5.38, SD=1.404), are aware of the problems associated with data quality (Mean=5.88, SD=1.304), they declare lower levels of proficiency in scripting (Python/R) (Mean=4.08, SD=1.889), advanced analytics (Mean=5.26, SD=1.638), and interpreting model outputs (Mean=4.23, SD=1.87). These results indicate that digital skill gaps have considered them one of the largest obstacles to successful AI implementation in education and employment. Capacity-building programmes are, therefore, critical towards the success of AI implementation.

Table 6: Individual Literacy and Technical Skills

Item	Section G: Individual Literacy and Technical Skills	Disagree (%)	Agree (%)	Std Dev	Mean	Median	Mode
G1	I understand the basic concepts of AI/ML (classification, regression, clustering).	24.4	75.8	1.404	5.38	6	6
G2	I am aware of issues related to data quality (bias, outliers, reliability).	11.8	88.1	1.304	5.88	6	6
G3	I can use analytical tools (advanced Excel/SPSS/PowerBI).	23.7	76.5	1.638	5.26	6	6

G4	I can produce basic scripts (e.g. Python/R) for simple analytics.	**59.0**	**41.0**	1.889	4.08	4	4
G5	I can interpret the model output and its limitations.	**54.8**	**45.3**	1.873	4.23	4	4
G6	I can design competency measurement instruments.	**51.3**	**48.6**	1.815	4.32	4	4
G7	I am skilled in using generative AI for Learning and Teaching documentation/research.	**39.6**	**60.5**	1.663	4.77	5	5
	Average %	**37.8**	**62.2**				

Perceived Impact and Value of AI/ML

Lastly, the participants are sure that AI/ML will significantly improve talent management in POLYCC-TVET, as the number of individuals who agree with it is 95.2% as shown in Table 7. AI will enhance efficiency (Mean=6.40, SD=1.190), in cycle time, enhance training precision (Mean=6.35, SD=1.106), and succession planning (Mean=6.37, SD=1.120), and greater organisational return on investment (ROI) (Mean=6.09, SD=1.245). The presence of high mean scores (6.09-6.40) in items regarding the impact clearly indicates a strong belief that AI will result in tangible quality improvement of decisions made, outcomes of staff development, and eventually the student learning experience. These impressions reflect the favourable ROI in institutions of AI-based HR analytics and educational decision systems.

Table 7: Perceived Impact and Value of AI/ML

Item	**Section H: Perceived Impact and Value of AI/ML**	**Disagree (%)**	**Agree (%)**	**Std Dev**	**Mean**	**Median**	**Mode**
H1	I believe AI/ML can reduce the cycle time of the career management/training process.	4.9	95.2	1.190	6.40	6	6
H2	I believe the accuracy of matching training to competency gaps will increase with the help of AI/ML.	3.5	96.6	1.106	6.35	6	6
H3	I believe AI/ML can improve the quality of succession planning decisions.	2.8	97.3	1.120	6.37	6	7
H4	PPPT job satisfaction has increased as a result of the use of AI in talent management programs.	4.2	95.9	1.135	6.34	6	7
H5	The impact on student achievement (proxy indicator) is positive.	5.6	94.5	1.169	6.16	6	6
H6	The cost-benefit value of Return on Investment (ROI) or Value on Investment (VOI) increases with the implementation of AI/ML elements in talent management programs.	7.7	92.4	1.245	6.09	6	7
	Average %	**4.8**	**95.2**				

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In general, the findings suggest that despite the high level of system efficiency, organisational readiness, and acceptance of AI, there are still major gaps in data interoperability, personal digital competencies, and the existing analytic abilities of the system that give apparent priorities to AI-based improvements of the e-SIS competency ecosystem.

DISCUSSION

The results of this research are also valuable clues about the preparedness, potential, and deficiencies related to the implementation of the artificial intelligence (AI) into the e-SIS competency system used to manage talent in POLYCC-TVET. A high level of overall agreement (85.3%) indicates a high level of institutional and user receptiveness to AI-enabled systems. The degree of preparedness corresponds to the global trends in education and TVET regarding the growing popularity of AI as an efficiency driver, personalisation, and data-informed decision-making (Kocabıyık, 2025). The high system efficiency score (95.3%) refers to the fact that the e-SIS platform already includes such core functions as data access, reporting and competency tracking, and this is the basis on which AI technologies may be embedded. This aligns with the literature that focuses on usability and maturity of a system as a precondition of successful integration of AI in education and HR analytics (Iancu and Oprea, 2025).

Nonetheless, the results also reveal technical infrastructure gaps and significant data preparedness, exceptionally in the form of API interoperability, metadata standards and computing resources. The results align with previous studies that indicate that AI integration in education is impossible without effective infrastructures with strong backend data systems that are capable of driving machine learning pipelines (Nasir and Jack, 2025). The lack of interoperability between the current institutional systems (e.g., HRMIS, SPMP, CIDOS) impedes the access to holistic and real-time data that is required to drive predictive modelling, recommender systems, and automated competency evaluation. This problem reflects the situation in the rest of the world with disconnected educational data ecosystems, which hinder the large-scale use of AI (Shvets et al. 2025).

The moderate score of the competency analytics (80.2%) indicates that despite its ability to detect the gaps of competency and justify the training decisions, the e-SIS has not sophisticated analysis features. Particularly, automated training suggestions and smart competency mapping are viewed as a downside by users. These results are also highly consistent with the studies that suggest the implementation of AI-driven recommender systems to facilitate personalised professional growth trajectories of educators and workforce members (França et al. 2023). These systems can contribute to precision, minimizing manual work, and continuous learning as the main pillars of contemporary talent management in Industry 4.0 and POLYCC-TVET ecosystems.

The readiness towards AI-enabled leadership development (82.2%) also has a hint of the possibility of AI implementation into leadership potential prediction, behavioural analytics, and competency-based succession planning. Although, users feel that e-SIS can facilitate the monitoring of KPIs and measurement of leadership development, they are not quite confident of the capability of the system to recognize high-potential leaders. This is consistent with the new literature suggesting the use of machine-learning models to increase the objectivity, early discovery and fairness of the process of choosing a leader (Jui and Rivas ,2024).

The most powerful enabling factor identified through the research is that there is an extraordinarily high AI/ML acceptance (98.2%), indicating a high level of cultural preparedness to digital transformation. This is reflective of the efforts by educators who have found that they are more likely to adopt AI when there are an apparent advantage and little disturbance to their teaching or administration methods (Zhang and Hou, 2024). These indicators of high acceptance levels indicate that behavioural resistance will not be a barrier to the adoption of AI in the POLYCC-TVET sector.

On the other hand, the least construct is individual technical literacy (62.2%), which is one of the most significant obstacles to a successful adoption of AI. The respondents are conceptually prepared in the fields of AI but do not possess practical abilities in such field as Python/R code writing, data analytics, and interpreting the model. This is consistent with more general international data, which indicates that the lack of digital competency and data literacy is one of the greatest obstacles in the application of AI-based educational systems (Tomczyk, 2025). The solution to these competency gaps will involve intensive capacity-building programmes, professional development of AI literacy, and practical training that will be consistent with future POLYCC-TVET educator competency frameworks.

Lastly, the high level of confidence of the respondents in the effects of AI (95.2%) such as increased efficiency, competency matching, and increased ROI adds to the worldwide evidence that AI-driven talent management systems can improve the workforce development outcomes under the condition of strong analytics and organisational preparedness (Rakesh and Upadhyay, 2025). The findings show that it is not only perceived value but also strategic opportunity for the system developers and policymakers to focus AI-driven improvements as part of the national POLYCC-TVET digital transformation agenda.

Overall, the discussion shows that the e-SIS system is technically stable and that users are very open to AI. However, for AI to be useful, data infrastructures need to be stronger, interoperability needs to be better, competency frameworks need to be standardized, and educators need to fill in their skill gaps. These results show that we need a full AI-driven talent management model that includes predictive analytics, smart recommendations, and leadership insights to help prepare the POLYCC-TVET workforce for the future.

CONCLUSION

This research offers a thorough, data-informed analysis of the preparedness, deficiencies, and strategic prospects for the incorporation of artificial intelligence (AI) into the e-SIS competency framework to improve POLYCC-TVET talent management in Malaysia. The findings indicate strong systemic foundations and user acceptance, evidenced by high levels of agreement regarding system efficiency (95.3%), AI/ML acceptance (98.2%), and the perceived impact of AI (95.2%). These results suggest that the POLYCC-TVET ecosystem is culturally and organizationally ready for AI-enabled change. This is in line with evidence that respondents are more likely to trust AI when they see clear functional and performance benefits (Zary and Zary, 2025). Moreover, e-SIS already shows strong usability and data accuracy, which are two (2) important things that need to be in place before machine learning models, recommender systems, and predictive analytics can be used in business decision-making (Forero-Corba and Bennasar, 2024).

There are still important problems that need to be fixed before AI-driven modules can be fully used, even by the people who are ready to use them. These include problems with data infrastructure, such as API interoperability, metadata standardization, and audit traceability, as well as big gaps in teachers' technical knowledge, especially when it comes to analytics and scripting skills. These problems are similar to problems that have been seen when it comes to using AI in education and the workforce. Poor data channels and a lack of digital skills make it hard to use AI on a large scale (James, 2021). To support long-term AI integration, we need to invest in data governance, targeted professional development, and improvements to system interoperability.

Conclusion, the results show that POLYCC-TVET system has a strategic chance to move toward a talent management model that uses AI. With strong user acceptance and system maturity already in place, e-SIS can evolve into a more intelligent platform that provides personalized training recommendations, automated competency gap analysis, leadership potential prediction, and real-time workforce insights capabilities that align with international trends in AI-driven HR analytics and skills development. The research provides empirical evidence essential for the development of an AI-driven POLYCC-TVET talent management model, guiding policymakers, system architects, and institutional leaders on the technological and human capital strategies needed to cultivate a workforce prepared for the future in POLYCC-TVET. Future studies should focus on making AI prototypes, doing pilot deployments, and looking at how they affect lecturer performance and institution outcomes over time.

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