Level of Usage and Perception Towards AI Applications Among POLIMAS Lecturers for Academic and Research Purposes

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Abstract: This research explores the extent of AI tool usage and instructors' perceptions towards artificial intelligence technologies at Politeknik Sultan Abdul Halim Mu'adzam Shah (POLIMAS) for educational and research purposes. Using a sample of 404 lecturers from different departments at POLIMAS, this study examined the determinants of AI technology acceptance, including the deployment of AI and the perceptions of teaching staff regarding the advantages and disadvantages posed by the incorporation of artificial intelligence in higher education. The results indicated that attitudes towards the applications of AI were favorable overall. Moreover, 66.4 percent of the respondents reported having used AI most frequently for the preparation of teaching materials and writing scholarly articles. Lecturers viewed technology positively, as it enhanced productivity (mean 4.21/5) and accelerated the preparation of teaching materials (mean 4.19/5). However, considerable challenges to adoption were noted, including the need for training (mean 4.41/5), inadequate technological frameworks, and ethical concerns regarding the credibility of information. Examination of AI usage indicated differences across departments and age groups, with younger faculty from more technologically oriented departments showing higher usage levels. Some important factors concerning artificial intelligence use include institutional trust, effectiveness, and resources offered by the institution. The analysis adds to the Malaysian polytechnic information perspective on AI adoption in higher education by suggesting additional strategies involving training, policy, and institutional framework development, as well as sharp ethics-focused boundaries designed for the specific positioning of POLIMAS academics.

Keywords: *artificial intelligence, higher education, faculty perceptions, academic technology adoption, Malaysian polytechnic education*

1.0 INTRODUCTION

The impact of Artificial Intelligence (AI) on the transformation of sociolocical paradigms is profound and higher education is no exception. Rising and transformative AI tools, especially generative AI apps, such as ChatGPT, Google Bard/Gemini, and Microsoft Copilot, have posed both opportunities and challenges for academic institutions. While these technologies focus on improving the processes of teaching, learning, and research, they also raise serious issues of scholarly dishonesty, ethics, and the changing role of educators (Shata & Hartley, 2025; Nikolic et al., 2024).

The accessibility of AI tools has made them more ubiquitous in higher learning institutions. McClain (2024) reported that for the first time, 43% of individuals aged between 18 to 29 claimed they had used ChatGPT, a noticeable increase from the 33% reported nine months earlier. This steep rise in the use of AI tools has compelled educational institutions around the world to consider how these technologies can be integrated into the educational framework and what implications they will have, either positive or negative, on academic work.

In Malaysia, POLIMAS along with other polytechnic educational institutions have started integrating AI technologies into their teaching and research functions. However, there is a gap in the literature on how lecturers in Malaysian polytechnic institutions perceive and employ AI technologies.

Analyzing the perceptions, usage, and concerns regarding AI among the faculty of an institution helps create supporting policies that promote the responsible use of artificial intelligence in education within the institution.

In order to bridge this gap, we can analyze POLIMAS lecturers' perceptions and usage of artificial intelligence (AI) applications as a case study. This study was guided by the following objectives:

1. Investigate how POLIMAS lecturers utilize AI applications in their academic and research activities.
2. Gather opinions from the faculty about the advantages, challenges, and social and ethical concerns.
3. Identify factors that determine the acceptance and use of AI applications in teaching and research.
4. Examine the changes and trends in AI usage and perceptions among various demographic and socioeconomic groups.
5. Identify the educational needs of the faculty for the effective implementation of AI technology.

With these objectives in mind, this study aims to provide additional resources and literature on the implementation of AI in higher education, focusing on polytechnics in Malaysia. The outcomes of this study will be useful for institutional and educational leaders, policymakers, and educational technologists who aim to utilize AI technologies while considering the concerns and needs of the faculty.

2. LITERATURE REVIEW

2.1 The Evolution and Integration of AI in Higher Education

The past decade has witnessed significant improvements in the field of educational technology, particularly with the emergence of generative AI tools. Although AI has been a subject of study for quite some time, the educational sector within the entire realm of higher education has been facing unprecedented challenges owing to the almost unconditional access to and use of generative AI tools. Such tools have gained widespread attention and understanding of how they can be integrated into the teaching and learning processes (Yusuf et al. 2024). Through generative AI tools, myriad possibilities have been opened up in domains that were initially confined to computer science and information management.

The scope of AI in higher education has its boundaries set with respect to higher learning institutions, including the design of customized learning programs, automated grading rubrics, management, and even research AI, with the sharpest of its edges in tools such as ChatGPT and similar

Generative AI (GenAI) applications (Biswas, 2023; Adiguzel et al., 2023). The deep learning models that ChatGPT and such new tools are based on or utilize are capable of producing human-like text, images, and even audio recordings, which are of great importance in teaching, learning, and research activities (Lim et al., 2023).

According to Chiu (2024), "the responsibility of teaching has now shifted to institutions of higher education, as they need to prepare students for a world that will be heavily reliant on AI." However, the influence of AI on quality of education and learning remains unclear. Some research findings suggest that the use of AI improves performance, at least in the short-term. There are also concerns that employing AI tools may impact overall understanding and skill acquisition if they turn into a "crutch" (Lim et al. 2023).

2.2 Faculty Perceptions and Adoption of AI Technologies

Perceptions of AI technologies by academic faculty impact the integration of such technologies into higher education institutions and define the success of its implementation. Recent studies focus on the gap in perceptions, concerns, and adoption behaviors of academic staff concerning the use of AI technology.

Barrett and Pack (2023) reported gaps among students and faculty about the appropriated scope of Generative AI within academic contexts, with instructors being more favorable toward its application than students. This gap suggests that some evolutionary shift from the longstanding concerns regarding technology adoption by faculty appreciating the pedagogical benefits of AI tools in teaching, albeit with challenges, is occurring.

Nikolic et al. (2024) undertook a systematic literature review and identified concerns of integration AI into education. Faculty were somewhat appreciative of AI's efficiency, recognizing its usefulness and applicability in instruction, but also raised significant concerns regarding academic integrity, accuracy, trustworthiness, skill level, proper utilization of imposition, exposure, institutional policies, and procedures. This faculty perception identified in the reviewed literature indicated an underlying requirement for the adoption AI technologies within education at higher learning institutions is institutional policies outlining ethical constraints.

Through the lens of qualitative interviews with university instructors, Al-Mughairi and Bhaskar (2024) explored the barriers and motivators affecting AI adoption in higher education. Among the motivating factors were the adoption and customization of new technologies into teaching, time efficiency, and career progression. At the same time, they pointed out five inhibiting factors as well, which include: worries regarding reliability and accuracy, diminished human engagement, data and privacy security issues, organizational apathy, and dependency on AI technologies.

2.3 Theoretical Frameworks for Understanding AI Adoption

There are many ways to approach incorporating AI into education. One of the oldest hypotheses, The Technology Acceptance Model (TAM), states that Perceived Ease of Use (PEU) and Perceived Usefulness (PU) significantly impact acceptance of a feature (Davis, 1989; Granić & Marangunić, 2019). These concepts enable discussion on how faculty members evaluate and adopt AI technologies.

The Unified Theory of Acceptance and Use of Technology (UTAUT) incorporated social influence and facilitating conditions as determinants that influence intention and goes further than TAM's focus (Venkatesh et al., 2016). This framework has multiple studies done on it in educational technology research, including AI adoption in higher education (Helmiatin et al., 2024). The UTAUT model specifies four domains, performance expectancy, effort expectancy, social influence, and facilitating conditions, which are the most crucial domains of technology adoption.

Social Cognitive Theory (SCT) approaches the adoption of technology from a different angle. Bandura (1999) explained that self-efficacy, social reinforcement, and the attitudes and behaviors related to technology are towered technology. To study the faculty perceptions and the adoption of generative AI, Shata and Hartley (2025) combined TAM and SCT, concluding that trust was the foremost predictor that influenced adoption decisions.

These theories assist in understanding the intricate details regarding the adoption of AI by faculty members at post-secondary institutions. Researchers studying faculty perceptions and behaviors concerning AI need to include perceived usefulness, social and AI easement, self-efficacy, and trust to formulate an accurate model of perception regarding AI systems.

2.4 Factors Influencing AI Adoption in Higher Education

More relevant factors concerning the application of AI technology by instructors at the college and university level have been defined by recent studies. Faculty perception AI trust issues constitutes one of the main factors since their willingness to accept any technology greatly depends on their perception of AI trust issues (Shata and Hartley, 2025). Trust relates to the social judgment accuracy and previous encounters with the involvement of AI systems trust, believability, credibility, and reliability influences affective disposition.

Perceived usefulness has been repeatedly identified as a stronger predictor of the adoption AI than reasoned ease of use (Shata and Hartley, 2025). Faculty members tend to adopt the use of AI technologies when its applicability is distinct in their teaching, research, or even administrative functions. This outcome shows that demonstrating the usefulness of technological aids is crucial in assuaging acceptance.

Social reinforcement along with peer influence shape faculty's perception of and interactions with AI technology (Shata & Hartley, 2025; Busken, 2020). The faculty is a social network, and, in turn, a social network of their discipline is composed of faculty members who are experts in a discipline. They are equally influenced by their peers and the social norms of the organization. This shift captures the problem in regards to the need to build communities of practice around AI.

As highlighted by Nikolic et al. (2024) and Al-Mughairi and Bhaskar (2024) it has already been noted that institutional support and facilitating conditions are among the most important factors governing the use of AI at the faculty level. Policies, training, and technology support are some of the resources that need to be available to assist faculty members in the transition to an AI-enabled academic setting. However, some studies have indicated that there is a more complex dynamic between institutional support and intention to adopt where some contextual factors moderate this relationship (Helmiatin et al., 2024).

Concerns pertaining to the ethics and risk factors associated with AI technology constrain faculty adoption (Al-Mughairi & Bhaskar, 2024; Yusuf et al., 2024). These include the reliability of the content presented, the integrity of academic work, privacy and data protection, and the impact AI has on students' pedagogical and professional skill development. Addressing these issues is necessary for the responsible application of AI in higher education.

2.5 AI Adoption in Malaysian Higher Education Context

Research on the integration of AI technology within Malaysian institutions of higher learning has been growing, but studies focusing specifically on polytechnics are still absent. As highlighted by Osman et al. (2024), insufficient training and support AI use optimization at the administrated intake AI policy needs-strategy level system AI policy use lead to policy AI use AI integration framework policies as they were formulated or not and are adopted by instructors at institutes of higher learning AI technology use considering its determinants for adoption through deep qualitative interviews AI Technology Inclusion through the lens of Malayan instructing is explained thinking. Secondary attention was directed towards the context with aim of explanation as to why technology is not being appreciated impacting adoption and integration frameworks employing comprehensive reasoning patterns at the integration levels considering structure determining frameworks. The frameworks provide policies learners focus their studies on technology, with more emphasis being placed on the research rather than the instruction.

In a research conducted by Jodi et. al (2024), the authors systematically reviewed the existing literature focusing on AI ethics at Work, concerning the applications of AI in the roles of lecturers in higher education and highlight key ethical concerns while suggesting some flexible boundaries which give autonomy, but also impose ethical limits on lecturers. This study reinforces an important gap regarding ethics in the use of AI in relation to higher education in Malaysia.

Yusnilzahri et al. (2024) conducted a systematic review of the functions and effects of ChatGPT in higher learning institutions in Malaysia, paying particular attention to the professional responsibilities of the teaching faculty in relation to the ethical application of AI in teaching and research. Their research captured the state of ChatGPT utilization in Malaysia and identified directions for future work.

As discussed in Saman et al. (2024), Saman focused on more global perspectives to analyze the role of AI in transforming Malaysian higher education in the wake of digitization. The study emphasized the need for effective planning for the implementation of AI technologies, which widened the scope for the application of AI in higher educational institutions in Malaysia.

These studies help comprehend the issues related to the use of AI technology within the framework of higher education in Malaysia. However, the case of polytechnic institutions, such as POLIMAS, with their distinctive academic profiles and organizational configurations, calls for more detailed inquiries to devise focused plans for the use of AI technology.

2.6 Research Gap and Contribution

Although the adoption of AI technology in higher education is being increasingly studied, there is still a lack of focus on the context of Malaysian polytechnics. First, there is a clear discrepancy in research related to polytechnic and university institutions due to differing educational purposes, staff demographics, and organizational frameworks. Second, there is a research gap that focuses on the demographic variables of AI adoption within a singular institution in Malaysia, specifically which academic disciplines and social characteristics are. Third, considering local culture and institutional settings, there is scant research on what drives polytechnic lecturers in Malaysia to adopt AI.

This study analyzes the perception and usage of AI among lecturers in ORDER, which fills the intellectual void mentioned above. This study enhances the understanding of Malaysian polytechnic education by investigating the factors determining AI adoption, usage, and faculty apprehensions across departmental and demographic divides. These results serve as a primary resource for advising institutional policy changes, faculty development initiatives, and investments in technology infrastructure aimed at improving POLIMAS and comparable institutions’ AI integration strategies.

3. METHODOLOGY

3.1 Research Design

This research employed a quantitative approach which included a survey for assessing the use and the views of AI tools by POLIMAS lecturers. With an intention of reaching all faculty members from different departments, backgrounds, and divisions, the survey method was selected. This approach aligns with prior studies focused on the use of technology in higher education institutions (Nikolic et al., 2024; Shata & Hartley, 2025) and helps to provide the rigor required to analyze intricate relationships between multiple variables.

3.2 Population and Sample

This study targeted the academic personnel of Politeknik Sultan Abdul Halim Mu'adzam Shah (POLIMAS), one of the top polytechnics in Malaysia. POLIMAS has a number of departments in its academic hierarchy which offer various technical and professional fields. Out of all the lecturers, 404 lecturers responded to the survey, which represents a considerable proportion of the institution's academic staff.

The respondents were drawn from various teaching departments.

- Jabatan Kejuruteraan Awam (JKA) - Department of Civil Engineering (n=91)
- Jabatan Kejuruteraan Elektrik (JKE) - Department of Electrical Engineering (n=78)
- Jabatan Kejuruteraan Mekanikal (JKM) - Department of Mechanical Engineering (n=56)
- Jabatan Matematik, Sains & Komputer (JMSK) - Department of Mathematics, Science & Computer (n=26)
- Jabatan Perdagangan (JP) - Department of Commerce (n=56)
- Jabatan Pengajian Am (JPA) - Department of General Studies (n=34)
- Jabatan Teknologi Maklumat dan Komunikasi (JTMK) - Department of Information Technology and Communication (n=32)
- Other Departments and Management Personnel (n=31)
- The sample also contains different age brackets.
- Highly Experienced (51 and above) - (n=89)
- Experienced (41-50) - (n=253)
- Mid-career (31-40) - (n=54)
- Young (30 and below) - (n=8)

The multidisciplinary sample provided an opportunity to investigate disparities in the use of AI and respondent attitudes in relation to different fields of study as well as in relation to the age categories of respondents.

3.3 Instrument Development

The data collection tool that was utilized included a questionnaire focused on measuring the perceptions and uses of AI technology among POLIMAS lecturers which was done using the literature on the usage of technology in higher education with a specific focus on the use of AI Technology (Shata & Hartley, 2025; Nikolic et al., 2024; Al-Mughairi & Bhaskar, 2024).

The questionnaire was organized into the following sections.

1. Demographic Information: This aimed at collecting data under the respondents' departments, age brackets, and other relevant demographics.
2. AI Knowledge and Usage: This studied the understanding and application of AI tools by lecturers for both academic and research purposes.
3. AI Applications and Purposes: This research looked at the different teaching, research, and scholarly writing activities that AI was used for and developed teaching materials for various educational and preparatory roles AI.
4. Perceived Benefits of AI: This examined the perceptions of lecturers on the usefulness of AI with regard to enhancing the efficiency and productivity of academic work.
5. Perceived Challenges and Concerns: This studied the respondents' concerns regarding ethics, copyright, accuracy, or other associated risks of AI technology.
6. Institutional Support and Training Needs: This assessed perceptions on the degree and nature of institutional support given towards the application of AI technology, as well as the investigation of support train needs.
7. Future Intentions: This explored lecturers' willingness to adopt and engage with AI technologies in the future.

All items capturing perceptions were constructed on a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree. This allowed distinctions between the varying degrees of attitudes and perceptions held by the faculty.

3.4 Data Collection Procedures

The data collection process was organized and carried out systematically to capture the entire scope of the institution. A formatting representation of all serving teaching departments in POLIMAS was used. To evaluate all possible avenues through which the survey can be accessed and is easy to complete, both online platforms and physical copies were made available. This approach ensures a greater turnout. Lecturers were surveyed as a pilot study; hence, prior to comprehensive implementation, the questionnaire was checked on a small population to understand its effectiveness and clarity.

Lecturers were sent reminders to participate, and thus, the entire collection period spanned multiple weeks until participation targets were hit. A sample of 404 people was representative, as almost all members of the POLIMAS academic staff were captured during the survey. Drawing from this sample provides insights into the utilization of AI and how it is perceived throughout the institution.

3.5 Data Analysis Techniques

The available information was analyzed using various tools to fulfill the objectives set earlier in this study. Observational metrics, such as means, standard deviations, and frequency distributions, were calculated to evaluate the overall understanding and attitudes of POLIMAS lecturers concerning AI.

Balanced analyses were conducted to evaluate how AI was utilized and understood in relation to different departments and age cohorts. These analyses incorporated analysis of variance (ANOVA) which ascertains whether distinct groups have different values for a particular variable.

Various factors were examined using correlational and regression analyses to determine the best predictors of AI adoption and usage. Such analyses deepened the understanding of the factors determining staff perceptions and behaviors towards AI technology through the lens of their disciplines.

Open-ended responses were evaluated through thematic analysis to provide more AI integration insights that were possibly overlooked due to rigidly crafted answers.

3.6 Ethical Considerations

This research preserved the ethical norms associated with educational research at all times. Voluntary participation and informed consent were obtained from the respondents. Respondents' anonymity and confidentiality were maintained throughout the research process. For analysis, data were anonymized and merged so that no personally identifiable information could be disclosed in the final results. Prior to conducting the study, institutional approval was received from the POLIMAS leadership. The aim of this research was to assist the institution in understanding how to improve AI utilization in academic work activities through informed insights, while upholding participant autonomy and privacy.

4. RESULTS AND FINDINGS

4.1 Demographic Profile of Respondents

The broad sample comprised 404 respondents from various faculties and age groups available at the POLIMAS. The departmental distribution of the respondents is provided in Table 1.

Table 1: Distribution of Respondents by Department

Department	n	%
JKA (Civil Engineering)	91	22.52
JKE (Electrical Engineering)	78	19.31
JKM (Mechanical Engineering)	56	13.86
JMSK (Mathematics, Science & Computer)	26	6.44
JP (Commerce)	56	13.86
JPA (General Studies)	34	8.42
JTMK (Information Technology & Communication)	32	7.92
Others	31	7.67
Total	**404**	**100.00**

The details of the distribution of respondents by age group are presented in Table 2, which reveals that most faculty members fall within the experienced (41-50) age bracket.

Table 2: Distribution of Respondents by Age Group

Age Group	n	%
Highly Experienced (51 and above)	89	22.03
Experienced (41-50)	253	62.62
Mid-Level (31-40)	54	13.37
Young (30 and below)	8	1.98
Total	**404**	**100.00**

4.2 Knowledge and Usage of AI Applications

The analysis showed that a reasonably high proportion of POLIMAS lecturers possessed knowledge regarding several applications of AI, achieving a mean score of 3.92 out of five (SD = 0.73). Table 3 illustrates the differences in AI knowledge between departments. JTMK (Information Technology & Communication) lecturers had the highest mean score of 4.22, while JMSK (Mathematics, Science & Computer) lecturers had the lowest mean score of 3.65.

Table 3: Knowledge of AI Applications by Department

Department	Mean	SD
JTMK	4.22	0.79
JP	3.93	0.71
JKA	4.01	0.64
JKE	3.82	0.68
JKM	3.86	0.67
JMSK	3.65	0.80
JPA	3.88	0.95
Overall	3.92	0.73

Concerning the practical use of AI tools, 66.4% of respondents indicated having used AI for the purposes of studying and conducting academic research. The average score (M = 3.83, SD = 0.82) suggests a moderate frequency of AI use on a 5-point scale. The values in Table 4 on the frequency of AI usage by department show that JTMK had the highest mean score of 4.00, and JMSK had the lowest mean score of 3.62.

Table 4: Frequency of AI Usage by Department

Department	Mean	SD
JTMK	4.00	0.80
JP	4.00	0.87
JKA	3.89	0.78

Department	Mean	SD
JKE	3.79	0.71
JKM	3.62	0.82
JMSK	3.62	0.82
JPA	3.94	0.92
Overall	3.83	0.82

Examining the data by age revealed that younger lecturers reported higher levels of AI knowledge and usage than did older lecturers, as shown in Tables 5 and 6.

Table 5: Knowledge of AI Applications by Age Group

Age Group	Mean	SD
Highly Experienced (51 and above)	3.74	0.73
Experienced (41-50)	3.90	0.72
Mid-Level (31-40)	4.20	0.65
Young (30 and below)	4.38	0.52
Overall	3.92	0.73

Table 6: Frequency of AI Usage by Age Group

Age Group	Mean	SD
Highly Experienced (51 and above)	3.61	0.82
Experienced (41-50)	3.85	0.83
Mid-Level (31-40)	4.10	0.76
Young (30 and below)	4.12	0.64

Age Group	Mean	SD
Overall	3.83	0.82

4.3 Purposes and Applications of AI Usage

POLIMAS lecturers claimed to use AI for a range of scholarly activities and research work. As seen in Table 7, which illustrates the average scores of AI applications, preparing teaching materials is AI's most common application, followed by academic writing and research.

Table 7: Purposes of AI Usage

Purpose	Mean	SD
Preparing teaching materials	4.19	0.69
Academic writing and research	4.12	0.75
Creating assessments and exams	3.95	0.82
Analyzing research data	3.52	0.89
Administrative tasks	3.88	0.78
Overall diversified usage	3.95	0.82

Differentiation in skills pertaining to prompt design and AI output assessment was evident among the lecturers with a mean score of 3.52 (SD = 0.89). As fostered proficiency appears to be at a moderate level, a further development program within the context of AI interaction is warranted.

4.4 Perceived Benefits of AI Applications

Most POLIMAS lecturers regarded AI applications in their academic and research activities as beneficial. The mean scores for different types of benefits are presented in Table 8.

Table 8: Perceived Benefits of AI Applications

Perceived Benefit	Mean	SD
Facilitates and expedites teaching material preparation	4.19	0.69

Perceived Benefit	Mean	SD
Improves research and academic writing quality	4.12	0.75
Enhances productivity and work quality	4.21	0.63
Provides user-friendly interface	4.07	0.69
Supports various academic activities	3.95	0.82

Lecturers in the technology-centric departments (JTMK, JKE, JKA) reported greater perceptions of AI advantages over other departments, with JTMK lecturers reporting the highest, with a mean of 4.25, that AI enhanced their teaching material preparation, while JMSK lecturers scored the lowest at 4.02.

4.5 Perceived Challenges and Concerns

Although there are advantages as perceived by POLIMAS lecturers, they also pointed out some challenges and concerns related to AI applications. The mean scores for challenges and concerns are listed in Table 9.

Table 9: Perceived Challenges and Concerns Regarding AI Applications

Challenge/Concern	Mean	SD
Ethical issues, copyright, and accuracy of AI-generated information	4.16	0.64
Reliability and credibility of information	3.96	0.73
Potential overreliance on AI	4.26	0.60
Privacy and data security	3.88	0.75
Impact on critical thinking and originality	3.92	0.71

Concerns regarding ethics, copyright, and accuracy received the most attention among other factors across all departments, with a mean value of 4.16 (SD = 0.64). This underscores the necessity to include fully integrated ethical frameworks in AI integration initiatives.

4.6 Institutional Support and Training Needs

The mean score for institutional support from AI integration at POLIMAS was 3.88 (SD = 0.70), indicating a moderate level of support. However, the lecturers indicated a great need for training in AI applications, with a mean score of 4.41 (SD = 0.60). The mean scores for institutional support and training needs subdivided into departments are shown in Table 10.

Table 10: Institutional Support and Training Needs by Department

Department	Institutional Support (Mean)	SD	Training Needs (Mean)	SD
JTMK	3.84	0.81	4.16	0.57
JP	4.16	0.63	4.46	0.57
JKA	3.82	0.61	4.44	0.64
JKE	3.82	0.70	4.41	0.59
JKM	3.71	0.65	4.36	0.55
JMSK	3.71	0.98	3.62	0.90
JPA	3.76	0.82	4.50	0.66
Overall	3.88	0.70	4.41	0.60

The elevated average scores for training needs across most departments suggest a notable requirement for professional advancement with respect to the application of AI in academic and research work.

4.7 Future Intentions for AI Usage

Based on the data collected, POLIMAS lecturers showed a high willingness to adopt AI in the future, with a mean score of 4.31 (SD = 0.56). A glance at Table 11 reveals the mean scores for future intentions by department.

Table 11: Future Intentions for AI Usage by Department

Department	Mean	SD
JTMK	4.28	0.68
JP	4.50	0.50
JKA	4.30	0.55
JKE	4.18	0.55
JKM	4.30	0.57
JMSK	4.27	0.45
JPA	4.38	0.55
Overall	4.31	0.56

Through correlation and regression analysis, the following factors were identified as crucial in predicting POLIMAS lecturers' adoption of AI technology:

1. **Perceived usefulness:** This was found to have a strong positive relationship with AI adoption ($r = 0.67$, $p < 0.001$) and exerted the greatest influence in the regression analysis, accounting for usefulness being the strongest predictor ($\beta = 0.48$, $p < 0.001$).
2. **Institutional support:** There was a strong positive relationship with AI adoption ($r = 0.52$, $p < 0.001$) and a significant predictor in regression analysis ($\beta = 0.31$, $p < 0.001$).
3. **Knowledge and skills:** There was a moderate relationship between support for AI adoption ($r = 0.49$, $p < 0.001$) and a significant predictor ($\beta = 0.28$, $p < 0.001$).
4. **Perceived ease of use:** This has some relation to AI adoption ($r = 0.42$, $p < 0.001$) but is a weaker predictor than perceived usefulness ($\beta = 0.19$, $p < 0.01$).
2. **Ethical concerns:** This factor was negatively correlated with AI adoption ($r= -0.34$, $p<0.001$), serving as a significant negative predictor ($\beta= -0.22$, $p<0.01$).

These findings support the TAM and UTAUT frameworks, emphasizing that usefulness has a stronger influence on perceived ease of use in technology adoption decisions. Furthermore, institutionally driven factors and ethical issues emerged as significant determinants of AI adoption among POLIMAS lecturers.

5. DISCUSSION

5.1 Knowledge, Adoption, and Usage Patterns of AI Applications

As revealed, most POLIMAS lecturers have a good understanding of AI applications, with 66.4% utilizing the technologies for academic and research purposes. This adoption figure is not different from the findings of some international studies, such as Shata and Hartley (2025), who indicated similar adoption percentages among university faculty members. Differences in knowledge and usage across departments indicate the impact of contextual discipline on technology adoption. Lecturers from more technologically oriented departments (JTMK, JKE, and JKA) demonstrated greater knowledge and usage levels, likely because of their greater exposure to and familiarity with technological innovation.

Secondary school teaching staff showed lower levels of AI knowledge and usage than did tertiary institutions. The combined experience and professional maturity of these lecturers probably encourages them to approach instructional technologies with skepticism and wait for proven effectiveness, which aligns with Van Dijk's theory of technology acceptance. Age-related differences in AI knowledge and usage align with patterns of technology adoption in earlier studies. Younger respondents indicated higher levels of AI knowledge and usage, which is in line with the generational differences in technology adoption studied by Nikolic et al. (2024) and Eaton (2025).

The main uses of AI by POLIMAS lecturers during the preparation of instructional documents, academic work, and assessment writing illustrate the usefulness of these technologies for a lecturer's workload. This is consistent with Al-Mughairi and Bhaskar’s (2024) analysis of AI adoption, which cites time-saving and personalizing instruction as primary drivers. On the other hand, the moderate skill level regarding prompt engineering and output assessment indicates a gap in the advanced AI literacy that faculty members seem to require.

5.2 Perceived Benefits and Challenges of AI Applications

Lecturers at POLIMAS claimed that the implementation of Artificial Intelligence (AI) technologies was advantageous to them with regard to their academic and research activities, especially concerning teaching material preparation as well as academic writing and productivity enhancement. The use of AI technology for record-keeping and writing in Al-Mughairi and Bhaskar’s 2024 work was attributed to advanced professional development and time saving, which corroborates this finding.

Perception of productivity and work quality that AI assists in or enhances (mean 4.21/5) indicates that POLIMAS lecturers value the contribution of technology to their work productivity. This supports Shata and Hartley’s (2025) argument that the most important reason AI is adopted stems from its usefulness rather than its ease of use. The means general opinion that AI assists in preparing teaching materials (mean 4.19/5), corroborating Biswas (2023) and Adiguzel et al. (2023) on the issue of AI custom and tailor-made applications for teaching resource preparation.

Even with these benefits in mind, POLIMAS lecturers reported apprehensions regarding AI applications, especially its ethical implications, copyright issues, and the precision of the information generated by AI (mean 4.16/5). This finding resonates with the concerns noted in previous studies conducted by Nikolic et al. (2024) and Jodi et al. (2024), who highlighted the ethical considerations of AI integration in higher education. The apprehension related to the potential overreliance on AI technologies (mean 4.26/5) corresponds to Al-Mughairi and Bhaskar's (2024) identification of overreliance as a primary inhibiting concern, demonstrating a faculty understanding of the balance required between technological support and human discernment.

The faculty's moderate concerns regarding privacy and data security (mean 3.88/5) indicate that these factors, while acknowledged, are not viewed as substantial obstacles to adoption when compared to other settings. This contrasts with Al-Mughairi and Bhaskar's (2024) findings, in which privacy and data security emerged as more salient issues, possibly illuminating differences in institutional context or regional disparities concerning data protection awareness.

5.3 Institutional Support and Training Needs

The mean evaluation of institutional support concerning AI integration within POLIMAS was 3.88, while the perceived need for training assistance was 4.41, suggesting a gap. This reinforces Nikolic et al. (2024) findings which assert that institutional support of training services fundamentally processes functions intended to address formally specified resources required to fulfil the needs created by integrating AI technologies. The particularly high expressed training needs from JP (4.46), JKA (4.44), and JKE (4.41) suggest that the non-technical focused sub-units may be less self-sufficient in harnessing AI technologies than previously thought.

Differences in support may reflect gaps in once-off departmental leadership, support resources, or cross departmental technological priorities. As such, a single overarching policy to foster AI integration at the school level may be less effective than one targeting the distinct features of different academic units. As Helmiatin et al. (2024) noted, the vigorous advocacy for these conditions can blend with other factors to supplant or impede related decision-making.

5.4 Factors Influencing AI Adoption at POLIMAS

The results regarding POLIMAS lecturers using AI tools relate most closely to the Technology Acceptance Model (Davis, 1989; Granić & Marangunić, 2019) on perception of usefulness, which Shata and Hartley (2025) built upon. This implies that greater consideration should be given to the effects of AI on productivity rather than its convenience in use. It also demonstrates how institutional support is the most important predictor and highlights the isssues active support AI integration policies ai as discussed by Nikolic et al. (2024) and Al-Mughairi and Bhaskar (2024).

The simultaneous ethical issues with AI adoption suggests that these gaps require attention from policy and ethics frameworks. That supports further Jodi et al. (2024) by suggesting that embracing unrestrictive ethical guidelines requires flexible controls from institutions. The weaker effects of knowledge and skill level on adoption imply that while training is needed, organizational support from top management is far more important.

The interrelation of these factors consolidates multifaceted phenomena concerning the adoption and integration of technology in the field of education, as mentioned in the literature, such as UTAUT (Venkatesh et al., 2016). This means that there is a need to balance integrating AI at POLIMAS with organizational policies and processes, faculty perceptions of use, support, ethical issues, and faculty understanding of AI.

5.5 Departmental and Demographic Variations in AI Perceptions and Usage

Differences in AI knowledge, usage, and perception across departments shed light on the social aspects of technology adoption. The relatively higher adoption rates from the JTMK and engineering departments indicate that departmental culture and prior exposure to AI technologies seem to have a bearing on the decisions that AI is adopted. However, the seemingly positive attitudes in all departments partially provide an indication for deeper support from the administration in all departments.

The differences in age concerning knowledge and use of AI reflect exposure to technology across generations but should not be taken as a foregone conclusion. The intention to adopt AI tools in the future across all age groups also suggests, in their respective silos, that the difference is attainable with appropriate training and support frameworks put in place – as illustrated by the overall mean score of 4.31 out of 5. This supports Eaton’s (2025) finding that while age might serve as the starting point for perceptions of information, the attitude employed in their perception of institutional aid and advantages outweighs thrusts and tends to ease age hurdles towards adoption.

The lack of perceived training requirements for the use of AI in teaching across departments emphasizes the need for focused and tailored professional development and training that addresses the needs of specific groups. More advanced concepts, along with the integration of ethical frameworks, would be beneficial for better-developed departments, whereas lower-performing departments such as JMSK would require a more fundamental approach. These findings are consistent with those of Osman et al. (2024) regarding the need for targeted optimization of AI utilization among Malaysian academics.

5.6 Implications for AI Integration in Malaysian Polytechnic Education

These strategies concerning the integration of AI technology into polytechnics in Malaysia have critical implications as underscored by the research findings. First, the predominant overall favorable perception and intent suggests a nurturing environment at POLIMAS and similar institutions in regard to future AI adoption and its prospects. Also, the uncovered faculty training gaps pointed out the need for more faculty development beyond the technical aspects to the ethical dimension as well. The gaps also show the differences within departments implying the need for additional AI integration strategies focused on particular disciplinary centers of excellence that more appropriately harness contextual strengths.

As highlighted earlier, the contribution of perceived usefulness to adoption decisions requires that something tangible be at the AI agenda's forefront. Saman et al. 2024 recommended learning from global counterparts while emphasizing the need to tailor approaches to fit the Malaysian narrative as critical to AI integration in higher education. Ethical and factual correctness issues also illuminate the need for strong innovation infrastructure policies and guidelines which are clear and well-defined at the institutional level.

The findings are consistent with Yusnilzahri et al. (2024) and Jodi et al. (2024) on the use of AI in Malaysian higher education with particular views from polytechnics. The emphasis of a polytechnic on the acquisition of practical skills and applied learning creates particular advantages and difficulties regarding AI integration when juxtaposed with other more research-intensive universities.

6. CONCLUSION

6.1 Summary of Key Findings

The aim of the study was to evaluate the extent of the use and perception of AI technologies by POLIMAS lecturers which indicates the adoption level of AI technologies in a Malaysian polytechnic institution. The major findings of this study are as follows:

1. AI applications. POLIMAS lecturers' AI application knowledge was regarded as moderately high (mean 3.92/5). In total, 66.4% of lecturers had used these technologies for academic and research purposes, although levels of knowledge and usage differed by department, with greater adoption in technology-oriented departments.
2. The main AI applications by POLIMAS lecturers were teaching-material preparation (mean 4.19/5), academic writing and research (mean 4.12/5), and assessment writing (mean 3.95/5). Creation of located prompts and evaluation of AI output were moderate (mean 3.52/5), indicating that more developed skills are needed.

3. POLIMAS lecturers perceived AI applications positively in relation to productivity and work quality (mean 4.21/5), facilitation of teaching-material preparation (mean 4.19/5), and enhancement of economically and academically important writing (mean 4.12/5). Perceived benefits were the motivating factors for adoption.
4. There is caution regarding ethical and copyright issues, AI information accuracy (mean 4.16/5), potential overreliance on AI (mean 4.26/5), and critical thinking impact (mean 3.92/5). These concerns directly affect adoption and underline the need for an ethical framework.
5. The level of institutional support for AI integration was moderate (mean 3.88/5), whereas the respondents strongly emphasized the need for training (mean 4.41/5). This disparity is a notable concern in institutional development.
6. The most prominent predictors for AI adoption included usefulness, institutional support, knowledge and skill level, ease of use, and ethical considerations. The strongest influencing factor concerning AI use was perceived usefulness, which shows that proven practical advantages are required.
3. Differences in perceptions and use of AI technologies were noted across departments and age groups, capturing the impact of the disciplinary context and generational differences. Nonetheless, all demographic groups showed high average ratings (mean 4.31/5) for the intention to adopt, indicating widespread enthusiasm for adoption.

6.2 Theoretical Implications

These findings add to the technology adoption theory within the scope of education in several ways. First, the findings confirm the Technology Acceptance Model (TAM) satisfaction through the importance of perceived usefulness in adoption decisions. Perceived usefulness, which dominates adoption decisions over ease of use, supports Shata and Hartley's (2025) research seeking practical benefits for value in technology adoption.

Second, the findings expand the scope of UTAUT by focusing on the interplay between facilitating conditions (institutional support), performance acuity (perceived usefulness), and effort acuity (perceived ease of use) matrices specific to AI adoption in a Malaysian polytechnic institution. The influential role of institutional support strengthens the linkage with the UTAUT framework while offering relevant contextual insights.

Third, the study helps fill the gap concerning ethical issues in technology adoption and how concerns regarding information integrity, copyright, and undue dependence impact instructional decision-making processes on the technology. These are gaps in the literature that focus on injustice in the theoretical framework of technology adoption, especially artificial intelligence in education.

Fourth, examining differences across departments and demographic groups provides insights into the circumscribed context of technology adoption. This emphasizes the need to understand adoption patterns in light of disciplinary cultures, levels of technological proficiency, and age cohort contexts.

6.3 Practical Implications

The results of this study may be used for the effective integration of AI technologies at POLIMAS and other institutions of a similar nature.

1. **Conducted Comprehensive Faculty Training Workshops:** Design faculty training workshops aimed at equipping participants with technical (prompting, output evaluation) and ethical skills relevant to their departments and knowledge levels.
2. **Form Policy Framework Guidelines:** Create institutional policies and procedures pertaining to the role of AI in teaching, researching, and assessing learning. Address concerns of ethics, copyright, information verification, and support for innovation.
3. **Demonstration of Practical Benefits:** Provide faculty with the opportunity to observe and demonstrate the practical use of AI within their disciplines. Success stories and practices must be shared across departments.
4. **Technical infrastructure and support:** Enhances the technical infrastructure and services offered to assist professors interested in exploring the application of AI technologies in their courses.
5. **Ethical Framework Development**: Create loose ethical guidelines to govern the use of AI that grants faculty freedom within institutional boundaries. Dealing with the issues of honesty, correctness, and credit.
6. **Strategies for Integrating Systems:** Formulate new integration approaches for each specific AI-enhanced department that takes advantage of pre-existing opportunities and meets particular needs. AI strategies should observe bounded differences across disciplines while achieving organizational integration.
7. **Communities of Practice Development:** Create communities of practice in which faculty members can report their experiences, issues, and innovations regarding AI applications. Such communities may enable colleagues to offer support and create social support structures for endorsements.

6.4 Limitations and Future Research Directions

This research was conducted within certain boundaries, which suggested additional areas of study. The first boundary identified was within a limited time frame. The research provided only a glimpse into user perceptions at a single point in time and did not examine trends over a more extended period. This study would have benefited from examining the patterns of AI integration and user perception over time through longitudinal studies.

The second limitation involves the self-perceived data used by the study. In this case, the study examined the faculty's beliefs about their use of artificial intelligence (AI). This may not be entirely representative of reality. Incorporating more objective evaluation methodologies, such as ethnographic studies of teaching with AI or analyses of lecture materials that integrate AI technologies, could improve accuracy and provide a more realistic picture.

The third limitation pertains to the institutional focus of this study. This was the only institution examined in this study, which raises concerns over their applicability in other settings. Conducting the same studies across different polytechnic colleges and comparing them with those in universities would reveal which contextual elements AI usage relies on, thereby enhancing the understanding of the topic.

The fourth limitation was only taking the faculty's stance into consideration, therefore excluding the students' viewpoints and voices regarding AI teaching integration. There is a need to investigate the shift in perception among faculty members compared to students and evaluate the learning dynamics after AI integration.

Fifth, the fast pace of evolution of AI technologies indicates that existing AI findings might not capture all possible applications or issues for new emerging technologies. There is a definite need for ongoing research due to the dynamic possibilities of AI developments and their impacts on higher education institutions.

Possible directions for future research are as follows.

1. Assessing the impact of different training methodologies on faculty AI literacy and ethics comprehension.
2. The effect of AI on student learning, engagement, and skills development in a polytechnic education paradigm.
3. The creation and implementation of ethical policies regarding AI in Malaysian higher education institutions.
4. Comparative research on the level of AI integration in various types of higher education institutions in Malaysia and abroad.
5. Sustained influence of AI adoption on faculty roles, teaching activities, and career progression within polytechnic education.

6.5 Concluding Remarks

This research provides insight into how POLIMAS lecturers have AI strategies incorporated into their work and the perceptions that determine their application of AI systems. It demonstrates an overall positive attitude which underscores a keen willingness towards deeper integration of AI applications while also identifying institution-specific improvement and intervention challenges.

The concern and understanding of faculty's professionally sensitive concerns revolving around newer advanced AI systems and their effects on service delivery in higher education institutions is critical for the construction of effective implementation models. This situational examination of the adoption of AI technologies in a Malaysian polytechnic contributes to the debate on policy, practice, and research for other like-minded institutions having similar systems.

To realize comprehensive AI integration within the remit of ethical innovation, technology and humanity, oversight by the institution and autonomy granted to faculty members has to be balanced. Acting upon and building towards identified gaps as well as POLIMAS's existing strengths positions the institution and others to capitalize on AI's potential for enhanced educational value and mission-aligned teaching, learning, and research within the institution's and the wider society's educational values.

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