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Exploring Generative AI Usage Patterns in Universities: Analysis and Guidelines for Sustainable Practices

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Abstract

Generative artificial intelligence (GenAI) is driving a technological revolution, significantly impacting education, with universities as primary beneficiaries. This study explores the varied use of GenAI among university users in Malaysia, examining its challenges and effects across different demographic groups. A mixed-methods approach, including literature review content analysis, and a survey of 290 respondents, was used, analyzed with tools such as SPSS 27, and NVivo. The findings show widespread GenAI use, particularly among younger users (under 25), as revealed by one-way ANOVA testing, which rejected the null hypothesis that age does not affect engagement. No significant gender differences were found, though users with a bachelor's degree were more engaged than those with higher degrees. The study also found no strong link between the duration of AI experience or weekly usage hours and engagement, although a trend suggests increased usage leads to higher engagement. The study highlights six negative impacts of excessive GenAI use, including weakened interpersonal communication skills, potential declines in academic performance, increased stress from dependency on technology, the undermining of traditional educational methods, encouragement of academic dishonesty, and loss of learning motivation and engagement. To address these issues, the research introduces practical guidelines and recommendations including promoting self-regulation, establishing GenAI policy frameworks, and enhancing AI literacy and community engagement.

Introduction

The rapid evolution of generative artificial intelligence (GenAI) technologies has profoundly impacted the educational landscape, introducing tools that redefine knowledge creation and dissemination across academic fields. Applications such as ChatGPT, Gemini, Stable Diffusion, and Dall-E offer significant benefits in education, including personalized learning, round-the-clock tutoring, and support for diverse learning needs (Dwivedi et al., 2023). These technologies, capable of generating text, images, and other media, have become invaluable in fostering a dynamic and interactive educational environment (Gkinko & Elbanna, 2023). However, their integration into academic settings is perceived as a double-edged sword. While they bring unprecedented efficiency and support to educational processes, they also introduce complex challenges and ethical dilemmas.

Issues such as diminishing critical thinking and academic integrity have become particularly contentious (Currie, 2023; Stahl & Eke, 2024; Yusuf et al., 2024). The growing over-reliance on AI for academic tasks has sparked debate over its impact on students' cognitive development and the potential for fostering over-dependence, which might diminish scholarly rigor and increase levels of GenAI over-engagement, potentially leading to addictive behavior r(Gupta et al., 2023; Singha & Singha, 2024; Wysocki et al., 2023).

Furthermore, there is a notable research gap in understanding the full spectrum of GenAI's implications within university ecosystems. Studies have primarily concentrated on the benefits and technological advancements, with less attention given to the longitudinal effects on educational practices and student behavior (Bouteraa et al., 2024; Makridakis, 2017; Stahl & Eke, 2024; Su & Yang, 2023). This oversight presents a critical vulnerability, as the lack of comprehensive, empirically based frameworks to guide the sustainable integration of GenAI technologies might lead to ethical dilemmas and educational disparities.

This research is motivated by the urgent need to address the negative impacts of GenAI excessive use and to propose robust practical guidelines that promote balanced, responsible, and healthy practices for GenAI applications in educational settings. The study aims to explore the varied impacts of GenAI on university users, identifying both the benefits and the risks associated with its adoption. By doing so, it seeks to fill the existing research gap by providing empirical evidence and strategic insights that can inform policy and operational guidelines.

In conclusion, this research provides a detailed analysis of the phenomenon of over-engagement and excessive use of generative AI applications among university users, along with the negative impacts resulting from it, based on specific demographic variables such as age, gender, and educational level. Additionally, this research introduces practical guidelines and recommendations to mitigate the negative impacts of GenAI and enhance the positive outcomes of its use in academia. The guidelines emphasize the necessity of a GenAI policy framework that fosters ethical practices, educational equity, and the maintenance of academic standards, aiming to balance the transformative potential of GenAI with the preservation of core educational values. Through a mixed-methods approach, combining quantitative surveys and qualitative content analysis, this study will contribute significantly to the discourse on AI in education, offering a pathway toward more responsible and effective use of technology in shaping the future of learning.

Scope Review on Previous Related Work and Re-emphasize Research Gaps

Figure 1 illustrates scope review analysis of 14 studies on AI in universities, categorized by year, methodology, and calls for further research, and Table 1 surmises all 14 studies’ main findings and recommendations. The studies span 2021 to 2024, with a notable concentration in 2023 and 2024, highlighting the growing interest in AI's impact on higher education. Qualitative methods dominate, with mixed methods also prominent, while quantitative methods are underrepresented. Ten studies call for expanded research on AI's impact across various university ecosystems and advocate for responsible AI practices.

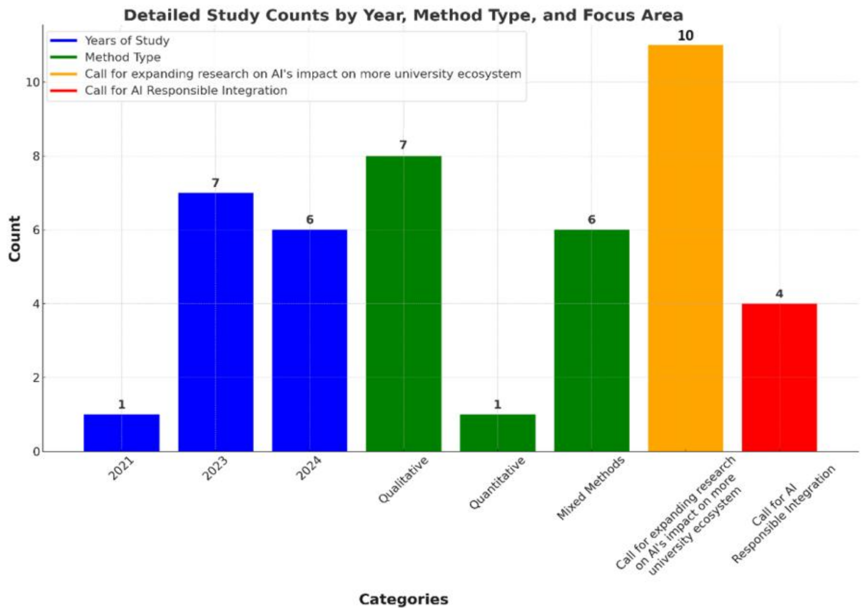

Figure 1. Scope Review on Gen AI Previous Related Work

Source: Developed by researcher

Table 1**.** Gen AI Scope Review Summary

Authors & Year	Study's Main Findings & Recommendations for Further Study
(Firat, 2023)	The study found significant potential benefits and challenges associated with AI integration in education, with a call for balanced and ethical implementation. The study recommends expanding research to include more diverse geographical and academic perspectives to more thoroughly investigate AI's long-term impact on education.
(Malinka et al., 2023)	The study shows that ChatGPT can handle university-level tasks effectively, producing responses comparable to typical student work. However, its use raises concerns about academic integrity and learning quality. Future research should examine the long-term educational effects of AI, develop strategies to detect and prevent its misuse, and conduct wider trials in various educational contexts to assess its overall implications.
(Yu, 2023)	While some top universities in the world have adopted a policy deciding to ban ChatGPT by prohibiting the use of ChatGPT or any other AI tools in exams unless specifically authorized (Y. Chen, 2023). This study on the other hand, supports not banning ChatGPT in academia, citing its potential to boost educational efficiency and adaptivity while preparing students for future tech environments and new ways of assessment. Yet, the study stresses the need for ethical usage guidelines and systems to maintain academic integrity, recommending more research into AI's long-term effects on learning.
(Farazouli et al., 2023)	The study shows differing acceptance and grades for AI versus student responses, suggesting AI impacts assessment standards and academic integrity. It calls for further research across disciplines and larger samples to fully understand AI's effects on educational assessment and long-term integration.

Authors & Year	Study's Main Findings & Recommendations for Further Study
(Perkins et al., 2024)	Findings showed challenges in detecting AI content using advanced prompting techniques. The performance of AI-generated content was comparable to that of students, suggesting AI tools can effectively mimic human writing in assessments. Further study on AI detection accuracy and on developing strategies to integrate AI tools ethically in educational settings was also suggested.
(George, 2023)	The study finds generative AI boosts graduate education by personalizing learning, offering detailed feedback, aiding research, and easing educator workloads, potentially enhancing outcomes and study completion. It recommends more research on long-term impacts, integration strategies, and overcoming AI limitations and misuse negative impacts.
(Krause et al., 2024)	The study shows students use ChatGPT mainly for assignments and exam prep, seeing it as beneficial but risky. It suggests strict policies, revised objectives, upskilled lecturers, adjusted curricula, and new exam methods to responsibly integrate AI. Future research should broaden to include diverse academic and geographical contexts and explore AI's long-term educational impacts.
(Ivanov et al., 2024)	The study found significant positive impacts of perceived strengths and advantages of generative AI on attitudes, subjective norms, and perceived behavioral control within the TPB framework. These factors positively influenced both lecturers' and students' intentions to use generative AI tools in higher education settings. Differences were noted in the perception of risks and weaknesses between students and lecturers.The study suggests further research to explore deeper insights into the use of generative AI tools.
(Dwivedi et al., 2023)	The study summaries generative AI's potential to enhance productivity and creativity but raises concerns about privacy, security, and misuse. It emphasizes the need for thorough research and strong policies to address these risks and suggests developing ethical guidelines for AI use.
(Barros et al., 2023)	The editorial outlines how generative AI is poised to transform academia across three primary areas: research, teaching, and service. The authors recommend a cautious and reflective approach to integrating AI, suggesting that future research should focus on both the opportunities and ethical challenges posed by AI in educational settings.
(Yan et al., 2024)	Effective collaboration between students and Gen AI enhanced students' meta-cognitive and self-regulated learning skills and positively impacted human-to-human communication. Difficulties in collaboration arose with complex tasks. . Future studies could explore broader academic applications and long-term impacts of student-AI collaboration.
(Dharmalingam et al., 2023)	The framework successfully predicted students at risk of poor academic performance by analyzing data from classroom activities and in-class assessments. It enhanced proactive interventions, significantly improving student engagement and performance by enabling timely support and personalized feedback. Future research should expand to multiple HEIs to validate the framework's effectiveness across different educational settings.
(Kuleto et al.,	Despite the potential benefits, the adoption of AI and ML in higher education also poses challenges such as data privacy concerns, the need for substantial infrastructure investments,

Authors & Year	Study's Main Findings & Recommendations for Further Study
2021)	and the risk of increased dependence on technology which could impact critical thinking skills and interpersonal interactions. Further studies should also examine the long-term impacts of AI and ML on educational outcomes and address ethical concerns related to data privacy and the potential dehumanization of education.
(Tajik & tajik, 2024)	The study highlights ChatGPT's role in creating engaging learning environments, enhancing administrative efficiency, and scaling personalized education. It calls for empirical testing to assess effectiveness and limitations, and studies on ethical implications, biases, and AI's impact on educational equity to ensure responsible, inclusive AI use in education.

Research Questions

This exploratory research aimed to answer the following four questions:

RQ1: What is the current state of GenAI app usage among users in Malaysian universities, and what top key factors motivate their use of these apps?

RQ2: What potential negative impacts are associated with the intensive use of generative AI apps among university users?

RQ3: To what extent are university users intensively using generative AI apps? Do demographic and selected variables significantly influence the intensive use of these apps among university users?

RQ4: What recommendations and guidelines can assist university users in overcoming the challenges and difficulties they encounter when using generative AI apps?

Research Method

Data Collection, sampling approach and Participant Inclusion Criteria

This research employed a mixed-methods approach, utilizing both qualitative and quantitative data analysis techniques as. Qualitative exploration delved into the collected textual data through content analysis and scope review. For quantitative analysis, descriptive statistics, t-tests, and one-way ANOVA were employed to generate descriptive summaries and conduct inferential hypothesis testing to explore relationships between variables. Figure 2 Illustrates the summary of this study research method. Data collection utilized a self-administered online questionnaire designed using Google Forms. The questionnaire was structured into three distinct sections. The first section gathered demographic and profile information about the respondents. The second section focused on measuring the level of intensive use of AI applications among university users, employing a 5-point Likert scale for response options. Finally, the third section addressed the impacts, problems, and challenges associated with intensive use of general AI applications, again utilizing a 5-point Likert scale. This comprehensive approach ensured the collection of rich data suitable for both qualitative and quantitative analysis.

To ensure the participants had relevant experiences, a purposive sampling strategy was employed, incorporating a snowballing distribution technique. This involved initially contacting a small group of lecturers and students from various Malaysian universities who met the research criteria. These initial participants were then asked to recommend others who also had experience using general AI applications. This referral process continued until a sufficient sample size was achieved (Becker et al., 2012). To maximize participation, researchers utilized WhatsApp, Facebook, and phone calls to distribute the questionnaire and send reminders. A total of 290 responses were collected, deemed adequate to address the research questions and generate meaningful descriptive and inferential analyses.

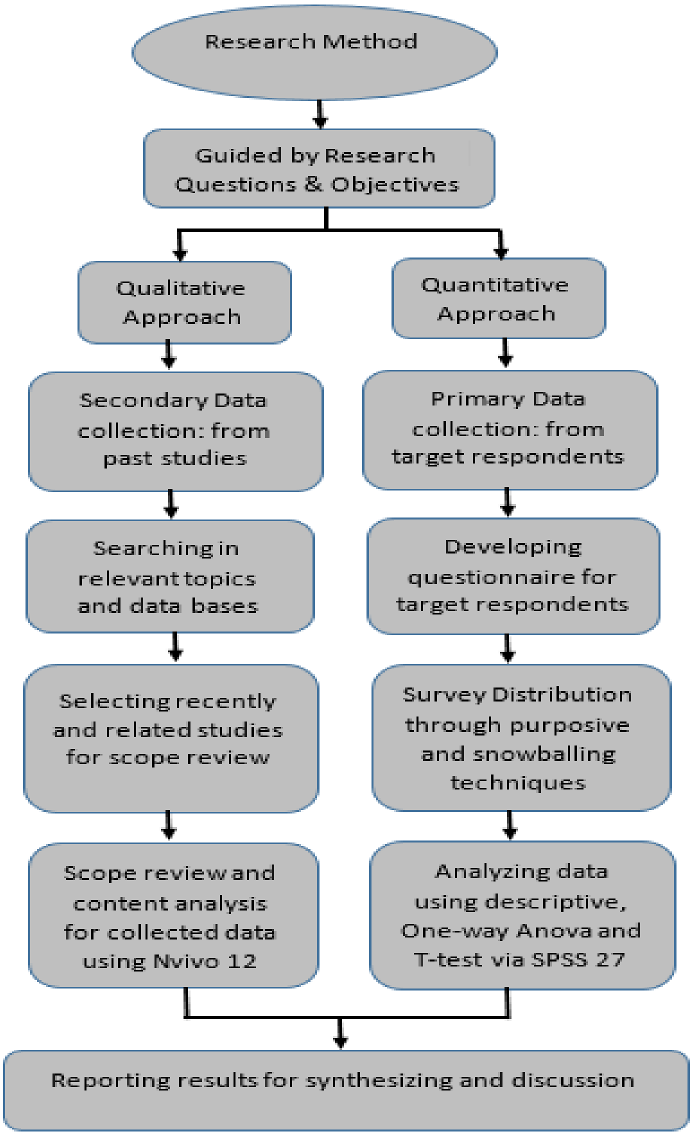

Figure 2. Research Method Illustration

Survey Development

The purpose of this research survey was threefold: Firstly, to gain clear understanding on the current state of GenAI app usage among users in Malaysian universities, and what factors motivate their use of these apps, Secondly, to measure the levels of General AI intensive use among university users based on demographic factors, Thirdly, to explore and evaluate potential negative impacts associated with intensive AI use. For assessing GenAI intensive and overuse, we employed 15 single-item variables adopted from previous studies in different contexts and utilized in this research as they listed and defined in Table 1 in this research Appendix, each representing a distinct dimension of GenAI Over-engagement, including Frequency, Disengagement, Preoccupation, Impact on Duties, Withdrawal, Preference, Unsuccessful Attempts, Defensiveness, Anxiety, Neglect, Escape, Need, Discomfort, Excitement, and Compulsivity, all rated on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). For evaluating negative impacts of intensive GenAI use, we listed 6 negative impacts and asked respondents to rate their agreement on them using a multiple-choice grid technique with the same Likert scale. To ensure content validity, the draft questionnaire that measure the levels of General AI intensive use among university users was reviewed by AI and educational technology experts, whose feedback refined the items for clarity, relevance, and comprehensiveness.

Data Analysis Process

To analyze collected data from secondary resources such past related studies, this research employed a two-step approach to analyze the data. First, we focused on qualitative analysis of existing research materials relevant to our topic. To gain a comprehensive understanding, we implemented a well-established method for analyzing information and its overall scope, as outlined by Creswell (Creswell, 2007) . This involved carefully sorting the collected information from past studies into relevant categories and then giving it a thorough re-reading. Next, we identified key points from these past studies as important sources for our research. Finally, we utilized specialized software called NVivo12 to analyze the information further and group it into common themes. This two-pronged approach ensured we leveraged both existing knowledge and fresh data from our survey to reach our conclusions.

To analyze collected data from primary source based on self-administrated online questionnaire, the data were analyzed using IBM's SPSS program, version 27 to obtain descriptive statistical methods (number, percentage, min-max values, mean and standard deviation), we performed a parametric t-test and one-way ANOVA was calculated to understand the relationships between different variables, the analysis was used to find the difference in multiple comparisons. A 95% confidence interval and $p < 0.05$ error level were considered in evaluating the results.

Results and Discussion

Participants' Demographic Information

The demographic data collected from respondents, as shown in Table 2, offers a detailed overview of the study population. The age distribution reveals a diverse range of participants, with the largest group being those under 25 years old (33.45%). This is followed by participants aged 35 to 44 years (27.93%), 25 to 34 years (25.52%), and a smaller group aged 45 to 54 years (13.10%). In terms of gender, the sample is predominantly male (61.03%), with females making up 38.97% of the respondents. Regarding educational qualifications, the majority hold a Bachelor's Degree (44.14%), followed by those with Master's Degrees (21.72%) and Doctoral Degrees (27.59%). A smaller portion of the respondents have other types of degrees (6.55%). The positions held by the respondents are varied: the largest group consists of undergraduate students (33.79%), followed by postgraduate students

(16.55%), lecturers (19.66%), administrative staff (10.69%), assistant researchers (2.41%), post-doctoral researchers (4.48%), and other positions (12.41%). This demographic diversity provides a comprehensive understanding of the various perspectives and experiences related to AI usage among university users.

Table 2. Demographics of Respondents

Demographics	Description	Frequency	(%)
Gender	Male	177	61.03
	Female	113	38.97
Age by Years	Under 25	97	33.45
	(25 to 34)	74	25.52
	(35 to 44)	81	27.93
	(45 to 54)	38	13.10
Education Level	Bachelor	128	44.14
	Master	63	21.72
	(Ph.D.)	80	27.59
	Other	19	6.55
Position	Bachelor student	98	33.79
	Post grad student	48	16.55
	Admin Staffs	31	10.69
	Lecturers	57	19.66
	Assistant Researcher	7	2.41
	Post-doctoral	13	4.48
	Others	36	12.41

Top Primary Purposes for Using GenAI Applications among University Users

Figure 3 illustrates the primary purposes for using AI generative applications among respondents. The most common use is educational, with 75.5% of respondents utilizing AI tools for teaching and learning. Research and data analysis follow closely, cited by 71.4% of participants, highlighting the significant role of AI in academic research. Content creation, including writing and multimedia production, is important for 54.1% of users. Personal interest and learning motivate 47.6% of respondents, while administrative and organizational tasks account for 23.4%. Generating income is the least common purpose, with only 10.3% using AI for financial gain. These findings suggest that universities should prioritize integrating AI tools into educational and research activities to enhance academic outcomes. Encouraging the use of AI for content creation can also support creative and multimedia projects. Providing resources and training for administrative tasks can streamline organizational processes. Furthermore, universities should support personal learning initiatives to foster continuous skill development among students.

Future research should explore the impact of AI on educational outcomes and research productivity. Investigating the effectiveness of AI in content creation and administrative tasks can provide insights into its broader applications. Additionally, examining the barriers to using AI for generating income could identify strategies to increase its adoption in entrepreneurial activities.

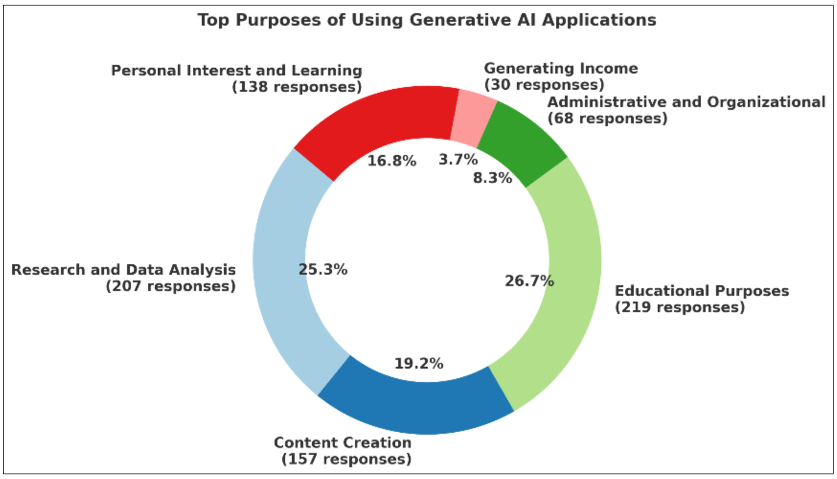

Figure 3. Purposes for Using AI Generative Applications

Source: Survey Results

Major Benefits Driving University Users to Engage with Generative AI Applications

Figure 4 illustrates the key benefits that motivate Malaysian university users to frequently engage with generative AI applications.

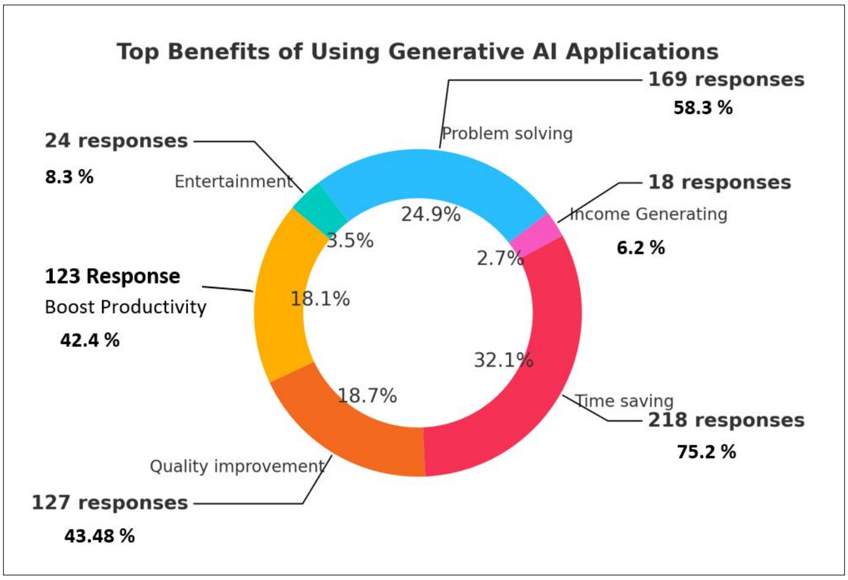

Figure 4. Top Benefits of Using Generative AI Applications

Source: Survey Results

A survey of 290 respondent’s shows that the most significant benefit is time-saving, chosen by 75.2% of users. Problem-solving capabilities are also highly regarded, with 58.3% of respondents highlighting this as a major advantage. Quality improvement (43.8%) and productivity enhancement (42.4%) are important factors that increase the appeal of AI tools. While entertainment (8.3%) and income generation (6.2%) are less prominent, they remain notable for certain users. These findings suggest that universities should focus on the time-saving and problem-solving advantages of AI applications in their academic and administrative activities. By integrating AI tools that boost productivity and improve quality, universities can foster a more efficient and effective learning environment. Emphasizing these benefits can encourage wider adoption and use of AI tools among students and staff. Future research should explore how specific AI tools contribute to time-saving and problem-solving across different academic disciplines. Investigating the effects of AI on productivity and quality improvement can offer deeper insights into their practical uses. Additionally, examining the potential of AI tools for entertainment and income generation could reveal new opportunities for their application in creative and entrepreneurial fields.

Negative Impacts of Generative AI Intensive Use in University Education

Figure 5 illustrates the perspectives of 290 university users on the negative impacts associated with the intensive use of generative AI applications, such as ChatGPT. The distribution of responses across five levels of agreement highlights significant concerns. For "Weakening of interpersonal communication skills," approximately 10% strongly disagree, 25% disagree, 20% are neutral, 20% agree, and 25% strongly agree. "Potential decline in real academic performance" shows around 3% strongly disagree, 15% disagree, 30% are neutral, 30% agree, and 22% strongly agree. The concern for "Increased stress from dependency on technology" has about 3% strongly disagreeing, 10% disagreeing, 15% neutral, 30% agreeing, and 42% strongly agreeing. Regarding the "Undermining of traditional educational methods," approximately 3% strongly disagree, 20% disagree, 20% are neutral, 25% agree, and 30% strongly agree. For "Encouraging academic dishonesty among students," around 3% strongly disagree, 15% disagree, 20% are neutral, 30% agree, and 30% strongly agree. Lastly, "Loss of learning motivation and engagement" sees about 5% strongly disagreeing, 20% disagreeing, 20% neutral, 25% agreeing, and 30% strongly agreeing.

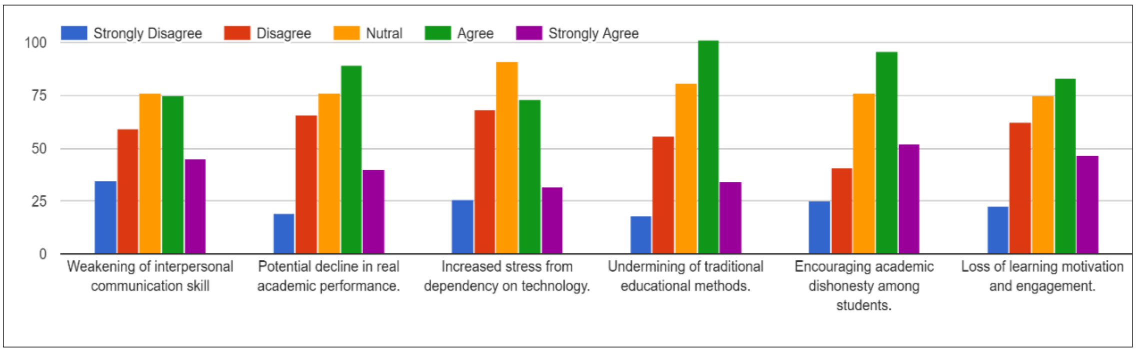

Figure 5. Generative AI Negative Impacts in University Education

Source: Survey Results

The majority of respondents express moderate to strong concerns (Agree and Strongly Agree) about these impacts. The most significant concerns are increased stress from dependency on technology (72% agree or strongly agree) and undermining traditional educational methods (55% agree or strongly agree). These findings suggest that while generative AI applications offer benefits, they also pose significant risks to communication skills, academic performance, and stress resulting from high dependency on GenAI technology, traditional education methods, academic integrity, and motivation. Future research should focus on longitudinal studies to monitor these impacts, develop strategies to mitigate negative effects, and explore educational interventions that can enhance positive engagement with AI tools while addressing these concerns. Addressing these impacts will be crucial to maximizing the benefits of generative AI in educational settings.

Measuring Intensive Use of Generative AI Apps in University Settings based on Selected Demographic Factors

This part of the results addresses the fourth research questions of the study. To answer the research question about measuring Intensive use of generative AI apps (by level of engagement) in University settings based on some demographic and selected variables whether they have any significant impact on intensive use of generative AI apps among university users, this presented results were based analyzed data collected through a survey of 290 respondents. Based on SPSS results, Table 3 below shows the descriptive output for respondents' demographic variables with level of Gen AI engagement. To measure level of Gen AI engagement among users, we utilize a 15-factor Likert scale, where each factor is measured on a 5-point scale. The total score is calculated by summing the individual responses, resulting in a quantitative measure of engagement ranging from 15 (minimal interaction) to 75 (potentially excessive engagement on Gen AI). Based on the total score, user engagement is categorized into four levels: Low (15-30), Moderate (31-45), High (46-60), and Over Engagement (61-75). This section and its subsections present the results and their interpretations, including implications and potential directions for future research.

Table 3. AI Level of Engagement across Different Demographics in University Settings

						95% Confidence Interval for Mean			
		N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Min.	Max.
Age vs AI_Level_Of_Eng_Tot_Scores	Under 25 Years Old	97	41.70	12.520	1.271	39.18	44.22	14	70
	25 - 34 Years Old	74	38.55	14.006	1.628	35.31	41.80	17	75
	35 - 44 Years Old	81	35.84	11.933	1.326	33.20	38.48	14	70
	45 - 54 Years Old	38	36.58	12.461	2.021	32.48	40.67	14	70
	Total	290	38.59	12.916	.758	37.10	40.08	14	75
Gender VS AI_Level_Of_Eng_Tot_Scores	Male	177	37.86	12.581	.946	35.99	39.72	14	70
	Female	113	39.73	13.400	1.261	37.24	42.23	14	75
	Total	290	38.59	12.916	.758	37.10	40.08	14	75
Level of Education vs. AI_Level_of_Eng_Tot_Scores	Bachelor Degree	129	41.65	13.473	1.186	39.30	44.00	14	75
	Master Degree	63	36.13	12.324	1.553	33.02	39.23	16	70
	PhD Degree	80	34.90	11.435	1.278	32.36	37.44	14	70
	Other Degree	18	41.67	11.832	2.789	35.78	47.55	24	70
	Total	290	38.59	12.916	.758	37.10	40.08	14	75
	Undergraduate stud	98	21.00	5.576	.563	19.88	22.12	6	30
	Postgraduate_ stud	68	21.85	4.585	.556	20.74	22.96	6	30
	Admin Staff	31	20.32	5.455	.980	18.32	22.32	6	27

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
						Lower Bound	Upper Bound		
Position vs. AI_Level_of_Eng _Tot_Scores	Lecturers	57	21.72	5.126	.679	20.36	23.08	8	30
	Others	36	21.50	6.408	1.068	19.33	23.67	7	30
	Total	290	21.33	5.358	.315	20.71	21.95	6	30
AI experience use vs. AI_Level_of_E ng_Tot_Scores	Less than 6 months	87	37.62	14.100	1.512	34.62	40.63	14	75
	1 Year Experience	144	37.70	11.901	.992	35.74	39.66	14	70
	2 Years' Experience	37	41.05	12.944	2.128	36.74	45.37	19	70
	More than 2 Years	22	44.09	13.348	2.846	38.17	50.01	19	70
	Total	290	38.59	12.916	.758	37.10	40.08	14	75
Time spent Weekly vs. AI_Level_of_Eng _Tot_Scores	Less than 1 hour	70	35.17	12.500	1.494	32.19	38.15	14	70
	1-2 Hours	96	38.09	13.449	1.373	35.37	40.82	14	75
	3-5 Hours	74	39.92	12.056	1.401	37.13	42.71	19	70
	6-7 Hours	29	41.24	12.144	2.255	36.62	45.86	18	70
	8-10 Hours	8	40.38	12.223	4.322	30.16	50.59	19	56
	11-13 Hours	5	42.60	5.595	2.502	35.65	49.55	35	50
	More than 13 Hours	8	48.25	18.148	6.416	33.08	63.42	18	70
	Total	290	38.59	12.916	.758	37.10	40.08	14	75

Gen AI Level of Engagement across Age Groups in University Setting

The results analysis of AI engagement among university users as shown in Table 4 and Illustrated in Figure 6 highlights varying interactions across age groups.

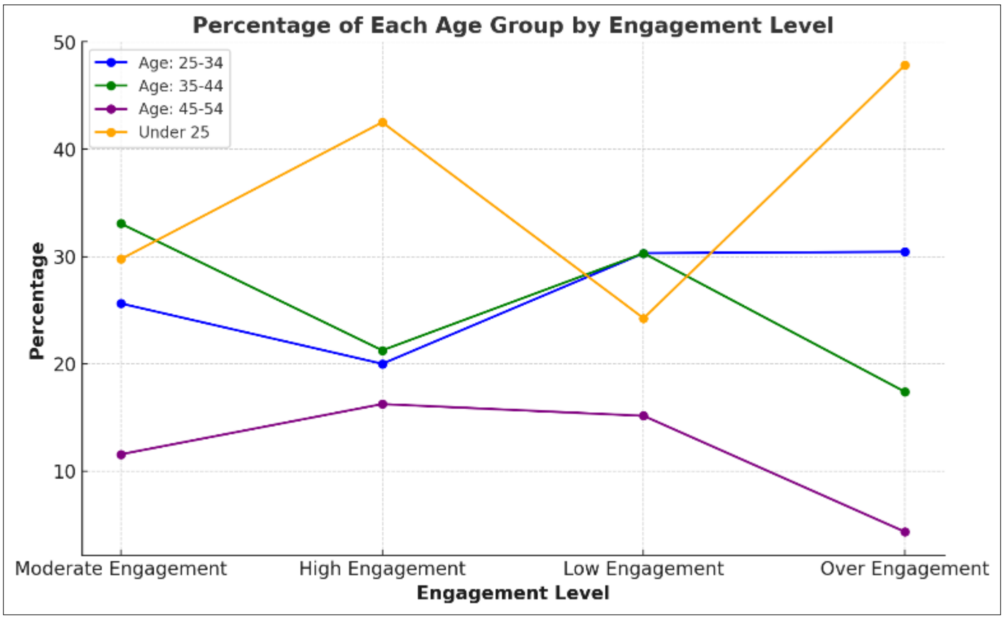

Figure 6. AI Engagement Levels Across Age Groups in University Settings
Source: Developed by Researcher

Younger users, especially those under 25, dominate the "High" and "Over Engagement" categories, indicating a higher risk of overuse due to their tech-savviness. This raises concerns about potential dependency, emphasizing the need for educational interventions to promote healthy usage. In contrast, the 25-34 age group, while evenly distributed across categories, peaks in "Low Engagement," suggesting either cautious use or underutilization of AI, possibly due to risk awareness. The 35-44 age group shows the highest presence in "Moderate Engagement," reflecting a balanced approach to AI use, serving as a model for integrating AI without overreliance. The 45-54 age group exhibits the least engagement, likely due to generational differences in technology adoption and a slower adaptation rate, highlighting a need for targeted training and motivation to integrate AI tools effectively.

AI engagement patterns across age groups require tailored approaches in education and organizations to maximize benefits and minimize risks. For younger users, implementing policies and curricula focused on responsible AI use and digital literacy is essential. Middle-aged cohorts would benefit from ongoing AI education and exposure to enhance productivity and competitiveness. Older users need inclusive training programs to build skills and confidence in using AI technologies. Overall, AI integration in education and professional development must adapt to these age-related trends to ensure effective digital education and workforce readiness.

Table 4. AI Level of Engagement Across Age Groups in University Settings

Engagement Level	**Total Scores Range**	**Number of Respondents**	**Percentage (%)**	**Age: 25-34 (%)**	**Age: 35-44 (%)**	**Age: 45-54 (%)**	**Under 25 (%)**	**Most Common Age**
Low Engagement	15-30	121	41.72	25.62	33.06	11.57	29.75	Between (35 to 44) Years old
Moderate Engagement	31-45	80	27.59	20.00	21.25	16.25	42.50	Under 25 Years Old
High Engagement	46-60	66	22.76	30.30	30.30	15.15	24.24	Between (25 to 34) Years old
Over Engagement	61-75	23	7.93	30.43	17.39	4.35	47.83	Under 25 Years Old

Gen AI Level of Engagement across Genders in University Setting

The visual and tabular analysis of AI engagement levels among university users as shown in Table 5 and Figure 7 reveals significant insights into behavioral patterns relative to gender. The data categorizes engagement into four distinct levels: Low (15-30), Moderate (31-45), High (46-60), and Over (61-75) based on the total scores from a 15-question Likert scale survey. The frequency table and corresponding line chart highlight a prevalent trend: male respondents generally dominate the lower three categories of engagement, representing 62.12%, 61.98%, and 62.50% of the Low, Moderate, and High engagement levels, respectively. Interestingly, the Over Engagement level, which indicates a potentially unhealthy level of AI interaction, shows a reversal in this trend, with female respondents accounting for a slightly higher percentage (52.17%) compared to males (47.83%).

This reversal is particularly noteworthy as it suggests that while more males may engage with AI at varying levels, females are more likely to reach levels of engagement that could be considered excessive. Such findings could imply underlying differences in how each gender interacts with AI technologies, potentially influenced by factors such as usage motives, emotional connections to technology, or even the types of AI applications used. The implications of these findings are multifaceted. From an academic perspective, understanding these engagement levels can help educators and administrators design interventions that are tailored to different engagement patterns, potentially curbing over-engagement where it is most likely to occur. Also, the data could serve as a basis for further research into the psychological and social factors that drive such disparities in AI engagement among genders. Critically, while the data provides a clear depiction of engagement across genders, it raises questions about the root causes of over-engagement among female users. This could reflect broader societal or educational dynamics, such as differential access to resources or varying pressures faced by students of different genders. So, universities might consider implementing supportive measures or educational programs that address these underlying issues, promoting a healthier and more balanced approach to AI usage. Overall, the analysis not only sheds light on current patterns of AI engagement but also emphasizes the need for targeted educational strategies and further research to understand and manage AI interaction effectively among university populations.

Table 5. AI Level of Engagement across Genders in University Settings

Engagement Level	Total Scores Range	Female n, (%)	Male n, (%)	Total
Low Engagement	(15-30)	25 (37.88%)	41 (62.12%)	66
Moderate Engagement	(31-45)	46 (38.02%)	75 (61.98%)	121
High Engagement	(46-60)	30 (37.50%)	50 (62.50%)	80
Over Engagement	(61-75)	12 (52.17%)	11 (47.83%)	23

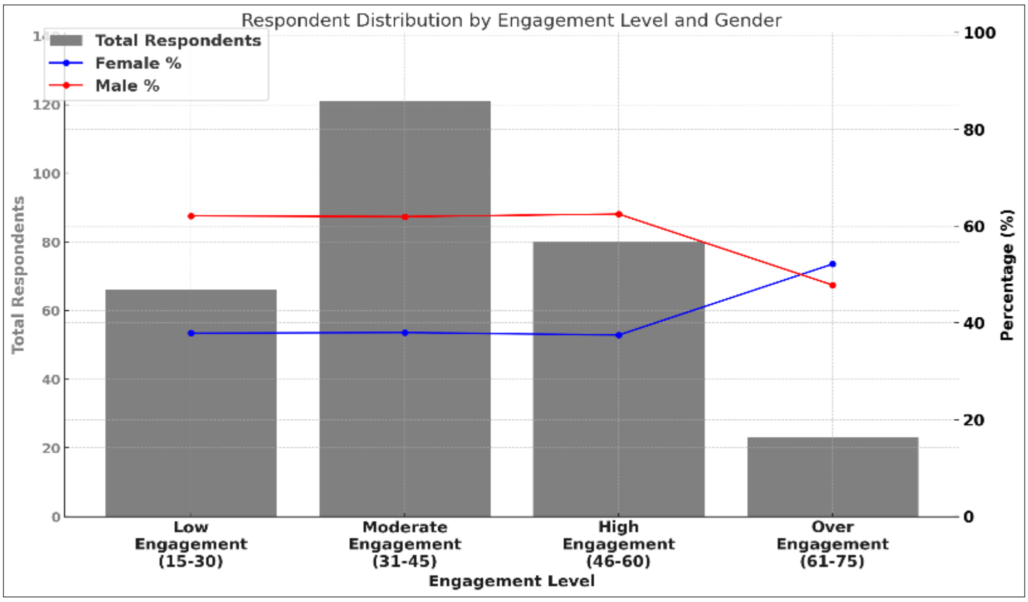

Figure 7. AI Engagement Levels Across Genders in University Setting

Source: Developed by Researcher

Analyzing Demographic Variables and Gene AI Level of Engagement Using One Way ANOVA Test

In the context of a university setting, a one-way ANOVA test offers a robust approach to examining the relationship between demographic factors and Gen AI engagement. This statistical method allows us to designate demographics, like age groups or gender, as independent variables. Gen AI engagement, on the other hand, serves as the dependent variable. Through ANOVA, we can statistically analyze whether there are significant variations in engagement levels across these demographic groups. Therefore, to gain valuable insights into how Gen AI use might differ among various student populations within the university environment, this research will employ a one-way ANOVA test. Furthermore, we will propose specific hypotheses for each demographic variable to investigate potential differences in relation to Gen AI intensive use or engagement levels.

Age and AI Engagement Levels

The ANOVA results as in Table 6 indicate a significant difference in AI Level of Engagement Total Scores across different age groups ($F = 2.731$, $p = 0.029$). This statistical evidence supports the observation that younger users, particularly those under 25 years old, are more engaged with generative AI applications compared to older users. The significant p-value (less than 0.05) allows us to reject the null hypothesis that age does not impact AI engagement levels. Instead, we accept the alternative hypothesis that age significantly affects AI engagement levels. This finding suggests targeted support and training for older age groups could enhance their engagement with AI tools. Further research should explore the underlying factors contributing to these age-related differences in AI engagement.

Hypothesis Testing:

- Null Hypothesis (H0): Age does not impact AI Level of Engagement.
- Alternative Hypothesis (H1): Age significantly impacts AI Level of Engagement.

Table 6. Age and AI Engagement Levels in University Settings

One Way ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Age vs. AI_Level_Of_Eng_Tot_Scores	Between Groups	1779.392	4	444.848	2.731	.029*
	Within Groups	46430.777	285	162.915		
	Total	48210.169	289			
Gender VS AI_Level_Of_Eng_Tot_Scores	Between Groups	242.665	1	242.665	1.457	.228
	Within Groups	47967.504	288	166.554		
	Total	48210.169	289			
Level of Education vs. AI_Level_of_Eng_Tot_Scores	Between Groups	2850.683	3	950.228	5.991	.001*
	Within Groups	45359.486	286	158.600		
	Total	48210.169	289			
Position vs. AI_Level_of_Eng_Tot_Scores	Between Groups	2181.717	4	545.429	3.377	.010*
	Within Groups	46028.452	285	161.503		
	Total	48210.169	289			
AI experience use vs.	Between Groups	1085.816	3	361.939	2.197	.089

One Way ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
AI_Level_of_Eng_Tot_ Scores	Within Groups	47124.353	286	164.770		
	Total	48210.169	289			
Time spent Weekly vs. AI_Level_of_Eng_Tot_ Scores	Between Groups	2028.671	6	338.112	2.072	.057
	Within Groups	46181.498	283	163.186		
	Total	48210.169	289			

Figure 8 illustrating the mean of AI Level of Engagement Total Scores across different age groups reveals a noticeable trend. Younger users, particularly those under 25 years old, show the highest mean engagement score at 42, which significantly drops to around 36 for the 35-44 age group before slightly increasing again for the 45-54 age group. This pattern suggests that younger university users are more intensively engaged with generative AI applications compared to older users. The decrease in engagement scores among middle-aged groups might indicate a shift in priorities or challenges in adapting to new technologies. These findings imply that targeted support and training for older age groups could enhance their engagement with AI tools. Further research should explore the underlying factors contributing to these age-related differences in AI engagement.

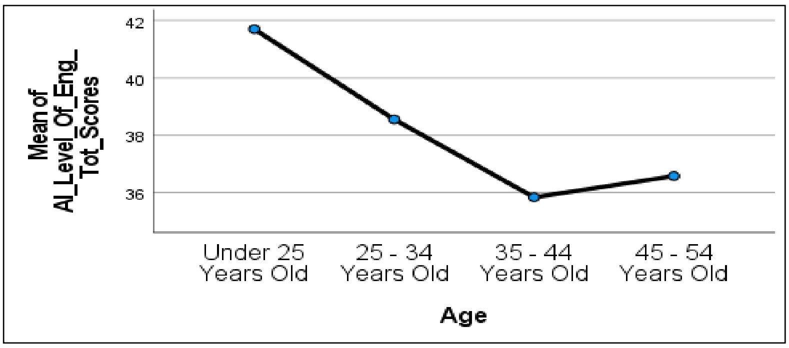

Figure 8. AI Engagement levels Across Genders in University Setting

Source: SPSS Output

Gender and AI Engagement Levels

The ANOVA results in Table 6 show no significant difference in AI engagement levels between males and females (F = 1.457, p = 0.228). This suggests that gender does not play a significant role in influencing engagement with generative AI applications among university users. The p-value greater than 0.05 indicates that we fail to reject the null hypothesis. While the observed data showed higher engagement among females, the statistical test does not support a significant difference. Future research should investigate other factors that might drive AI engagement beyond gender.

Hypothesis Testing:

- Null Hypothesis (H0): Gender does not impact AI Level of Engagement.
- Alternative Hypothesis (H1): Gender significantly impacts AI Level of Engagement.

Figure 9 shows the gender comparison in AI engagement levels indicates a higher mean score for females (around 40) compared to males (approximately 38). This suggests that female university users might be more engaged with generative AI applications than their male counterparts. The difference, although not very large, could be influenced by varying attitudes towards technology adoption and use between genders. Understanding these differences is crucial for developing gender-inclusive AI tools and resources. Future research should investigate the specific factors driving higher engagement among females and how these can be leveraged to support all users effectively.

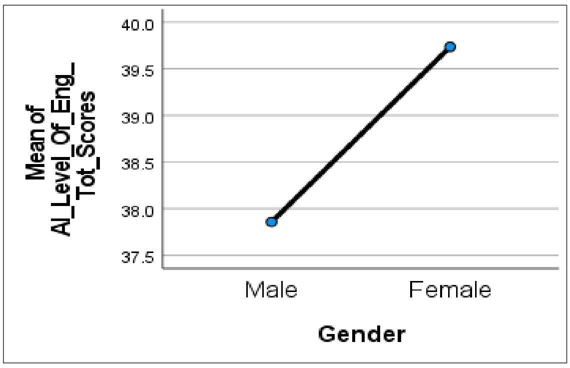

Figure 9. AI Engagement Levels Across Genders in University Setting
Source: SPSS Output

Educational Attainment and AI Engagement

In Table 6, the ANOVA results reveal a significant difference in AI engagement levels based on the level of education (F = 5.991, p = 0.001). This supports the observation that users with a Bachelor's degree are more engaged compared to those with a Master's degree, PhD holders, and those with other degrees. The p-value (less than 0.05) allows us to reject the null hypothesis and accept the alternative hypothesis that educational attainment significantly impacts AI engagement levels. These insights highlight the need for tailored AI training programs for different educational levels.

Hypothesis Testing:

- Null Hypothesis (H0): Educational attainment does not impact AI Level of Engagement.
- Alternative Hypothesis (H1): Educational attainment significantly impacts AI Level of Engagement.

Figure 10 comparing AI engagement scores across different educational levels shows that users with a Bachelor's degree have the highest mean score (around 42), while those with a Master's degree exhibit the lowest engagement (approximately 35). PhD holders and individuals with other degrees have intermediate scores. This variation suggests that the level of formal education influences engagement with generative AI, with Bachelor's degree holders being the most engaged. The lower engagement among Master's degree holders might be due to increased workload or different professional focus. These insights highlight the need for tailored AI training programs that cater to the specific needs and constraints of users at different educational levels. Further research should examine the reasons behind these differences to enhance AI engagement across all educational backgrounds.

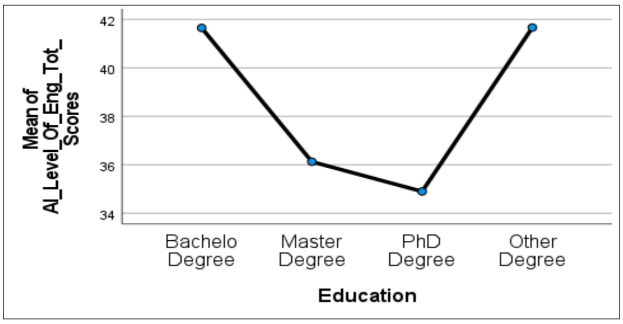

Figure 10. AI Engagement Levels Across Level of Education in University Setting

Source: SPSS Output

AI Experience and Engagement Levels

The ANOVA results as shown in Table 6 and Figure 16 for AI experience indicate no significant difference in engagement levels (F = 2.197, p = 0.089). This suggests that the duration of AI experience does not significantly impact engagement levels among university users. The p-value greater than 0.05 means we fail to reject the null hypothesis. Although the trend showed increased engagement with longer AI experience, it was not statistically significant. Further research should delve deeper into the factors that influence engagement beyond mere experience duration.

Hypothesis Testing:

- Null Hypothesis (H0): AI experience does not impact AI Level of Engagement.
- Alternative Hypothesis (H1): AI experience significantly impacts AI Level of Engagement.

Figure 11 depicting AI engagement scores based on the duration of AI experience shows a clear upward trend. Users with less than six months of experience have a mean score of around 38, which steadily increases to 44 for those with more than two years of experience. This indicates that longer exposure to AI applications correlates with higher engagement levels. It underscores the importance of sustained interaction and familiarity with AI tools to maximize their benefits. These findings suggest that encouraging continuous use and providing long-term support for AI applications can significantly boost user engagement. Future research should focus on identifying the specific learning curves and barriers experienced by new users to improve their onboarding process.

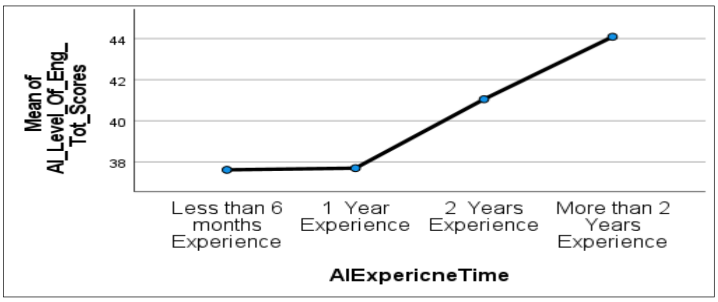

Figure 11. AI Engagement Levels Across Level of Experience Working with Gen AI

Source: SPSS Output

Weekly Usage Hours and AI Engagement

The ANOVA results for weekly usage hours show a marginally non-significant difference in AI engagement levels ($F = 2.072$, $p = 0.057$). This suggests that while there is a trend indicating higher engagement with increased weekly usage hours, it is not statistically significant at the 0.05 level. The p-value being close to 0.05 indicates a potential trend that could become significant with a larger sample size. This emphasizes the importance of promoting consistent usage habits among university users to enhance their proficiency with AI applications.

Hypothesis Testing:

- Null Hypothesis (H0): Weekly usage hours do not impact AI Level of Engagement Total Scores.
- Alternative Hypothesis (H1): Weekly usage hours significantly impact AI Level of Engagement Total Scores.

The ANOVA results provide a statistical foundation for understanding the factors influencing AI engagement among university users. Age and educational attainment significantly impact engagement levels, while gender, AI experience, and weekly usage hours do not show significant effects, though weekly usage hours approach significance. These findings suggest targeted interventions and further research to optimize AI engagement in educational settings.

Figure 12 illustrating the relationship between weekly usage hours and AI engagement scores reveals a positive correlation.

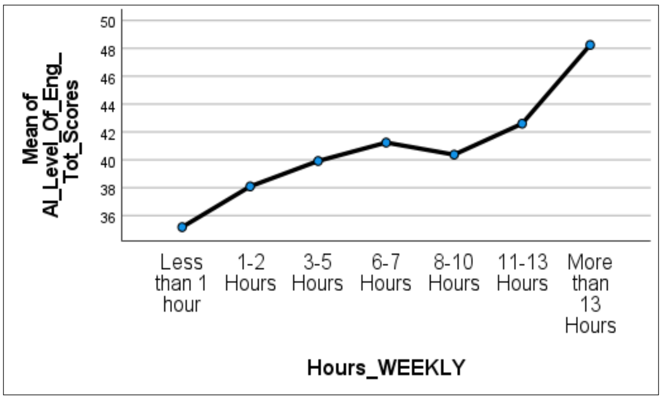

Figure 12. AI Engagement Levels Across Level of Experience Working with Gen AI

Source: SPSS Output

Users who spend less than one hour per week on AI applications have a mean score of around 36, while those using AI for more than 13 hours weekly reach nearly 50. This substantial increase highlights that more frequent use of AI tools leads to higher engagement levels. It suggests that regular and intensive interaction with AI is key to realizing its full potential. These insights emphasize the need for promoting consistent usage habits among university users to enhance their proficiency and engagement with AI applications. Further research should investigate optimal usage patterns and strategies to encourage regular interaction with AI tools.

Practical Guidelines for Sustainable and Healthy AI Practices in University Settings

The increasing use of generative AI in university settings has introduced a range of common problems, risks, and challenges, including over dependency that leads to excessive use that might affects some user's mental health, and raise ethical concerns, and the need for proper digital literacy. To address these issues and ensure students' sustainable well-being, we introduce practical guidelines and recommendations to promote healthy AI practices. These practical guidelines as follow: encouraging self-regulation skills, digital detox practices, as an individual level guidelines with policy support, training support as organizational and institutional level and AI technology literacy, community engagement and sustainability practice awareness as technology and environment level. This research proposed these practical guidelines and recommendations as an effort to provide a comprehensive mitigation framework that supports students and users in managing AI usage effectively in university settings by fostering a balanced approach that enhances their academic performance, mental health, and ethical awareness in the digital age.

Empowering Academia with Comprehensive GenAI Training and Best Practices

The emergence of Generative AI (GenAI) demands thorough training for students and university users to ensure balanced AI usage. Researchers underscore the importance of digital literacy and holistic competencies in education (Xia et al., 2024). Chan's (2023) study on the AI Ecological Education Policy Framework emphasizes enhancing AI literacy through pedagogical, governance, and operational dimensions(Chan, 2023). Effective training should encompass ethics, data privacy, and security, enabling educators to design robust assessments and evaluate problem-solving skills beyond AI proficiency (Xia et al., 2024). Upholding academic integrity requires faculty to detect AI-generated content and adapt their assessments accordingly (Perkins et al., 2024). Workshops and webinars can promote responsible AI usage, positioning AI as an educational tool rather than prohibiting it (Razi et al., 2024). Universities are broadening training programs to address GenAI's impact on pedagogy and learning, with a focus on ethical considerations (Plata et al., 2023). Ensuring equitable GenAI use necessitates support for low-resource districts and culturally inclusive models (Razi et al., 2024). Integrating AI projects and interdisciplinary workshops into curricula equips students to use AI effectively (Vukmirovic, 2024). Continuous professional development for educators and adaptive learning designs are vital to keeping academia relevant amidst technological advancements (Alrayes et al., 2024; Kurtz et al., 2024). Consequently, GenAI training is crucial for fostering healthy, ethical, and balanced AI usage.

Promoting Self-Regulation in the Context of Generative AI

The importance of self-regulation for students and university users in the context of Generative AI (GenAI) is critical for promoting healthy, sustainable, and balanced AI usage. Studies on digital detox reveal that improved self-regulation skills can significantly enhance attention control and reduce symptoms of depression and anxiety (Liao, 2019; Radtke et al., 2022). As AI becomes more integrated into education, self-regulated learning—which includes goal setting, self-monitoring, self-assessment, and adaptive learning strategies—becomes increasingly crucial (Xia et al., 2024).Deficient self-regulation has been identified as a core factor in technology addiction, manifesting through behaviors like internet addiction and excessive smartphone use (C. Chen et al., 2021). Even individuals without significant technology dependency can struggle with habitual technology use due to temporary lapses in self-regulation, highlighting the need for targeted interventions (Soror et al., 2012). Additionally, self-regulation and loneliness are significant antecedents of smartphone addiction, with research indicating that a lack of self-regulation can exacerbate addictive behaviors (Mahapatra, 2019). The positive correlation between deficient self-regulation and technology addiction underscores the need for interventions that enhance self-regulatory skills (Washington, 2021). Therefore, fostering self-regulation in GenAI users is essential to promote healthy, ethical, and balanced AI usage. Integrating self-regulated learning strategies into AI education and developing targeted interventions to address habitual technology use are critical steps in managing the impact of AI in educational environments. These approaches can help mitigate the negative effects of technology addiction and ensure that AI is used in a sustainable and balanced manner.

Importance of promoting Digital Detox for Balanced and Healthy AI Usage

Digital detox is crucial for students and university users to maintain a healthy, sustainable, and balanced engagement with AI, including Generative AI (GenAI). Reducing online time and regularly taking breaks from digital devices can mitigate the negative impact of perceived digital overuse on well-being (Mirbabaie et al., 2020; Turner et al., 2021). Research highlights the significance of digital detox in enhancing attention control and reducing stress, recommending strategies such as establishing tech-free zones and using basic phones to improve academic performance and emotional intelligence (Numanovich & Abbosxonovich, 2020). Digital detox entails deliberate breaks from electronic devices to focus on real-world interactions, which reduces stress and strengthens social connections (Nguyen, 2022; Radtke et al., 2022). It also assists in managing digital addiction by promoting better self-regulation and awareness of technology use (Cueto, 2023; Miksch & Schulz, 2018). The necessity of digital detox became more evident during the pandemic, with increased screen time due to distance learning and work, underscoring the importance of incorporating digital detox practices into daily routines (Nypadymka, 2022).Embracing digital detox as a regular practice can empower individuals to control their use of digital devices, including GenAI, ensuring technology serves them rather than dominates them (Vishwakarma, 2022). By integrating digital detox strategies, users can maintain a balanced relationship with GenAI, promoting overall well-being and preventing over-reliance on technology.

Role of University in Community Engagement for Promoting Balanced Generative AI Usage

Community engagement is crucial for encouraging the healthy, sustainable, and balanced use of Generative AI (GenAI) among students and university users. Activities such as service-learning and social entrepreneurship enable students to develop a sense of civic responsibility and place attachment (Bramwell, 2014; Lovett & Chi, 2015). By combining community engagement with nature-based solutions and establishing partnerships, universities can align with sustainable development goals, thereby enhancing both ecological literacy and community well-being (Toner et al., 2023). Universities are essential in fostering community engagement through collaborations that address societal needs, encourage knowledge exchange, and promote behavioral and economic changes. Action research and strategic partnerships within community-engaged learning practices can advance socio-cultural and economic equity while enhancing critical thinking and problem-solving skills (Catherine et al., 2018; Tijsma et al., 2023). Participating in community-based participatory research and collaborative projects not only transforms academic curricula but also prepares students to be active, socially responsible citizens who contribute to social change (Catherine et al., 2018). Thus, community engagement serves as a powerful means to leverage GenAI usage by creating environments that foster ethical, sustainable, and balanced practices.

Incorporating AI Literacy in Education and University Settings

Generative AI (GenAI) technology literacy is essential for promoting the healthy, sustainable, and balanced use of AI among students and university users. The integration of AI in education highlights the need for self-regulated learning, supported by comprehensive AI and digital literacy training (Xia et al., 2024). Critical thinking, creativity, and problem-solving skills should be explicit learning outcomes to ensure that both students and teachers understand the capabilities and limitations of AI (Xia et al., 2024).

AI literacy enables users to effectively utilize these tools across various disciplines, preparing them for an AI-driven future (Chan & Hu, 2023). Educational institutions should develop AI-focused courses and professional development programs that highlight ethical AI use, critical evaluation of AI-generated content, and the identification of biases (Vukmirovic, 2024). Continuous professional development is essential for keeping educators informed about emerging technologies and integrating responsible AI practices into education (Perera & Lankathilake, 2023).Incorporating AI literacy into curricula allows universities to empower students to fully leverage AI's potential while encouraging ethical and responsible use (Bozkurt, 2023). Ultimately, promoting GenAI technology literacy ensures that students and educators become discerning, responsible users, utilizing AI for positive and sustainable outcomes.

The Necessity of Policy Support for Generative AI in Education

Effective policy support is vital for ensuring the healthy, sustainable, and balanced use of Generative AI (GenAI) in education. Higher education institutions must continually design and revise policies and curricula to address the transformative impact of GenAI, ensuring equitable access and adapting to changing educational needs (Xia et al., 2024). Developing an AI Ecological Education Policy Framework, as proposed by earlier researchers, involves pedagogical, governance, and operational dimensions, stressing the importance of comprehensive AI literacy training for teachers, staff, and students (Chan, 2023). Involving experts from various fields is crucial to formulate policies that tackle the complex nature of AI in education, ensuring its ethical and responsible use (Duran & Ermiş, 2024). Institutions need to rethink assessment policies to incorporate GenAI's capabilities, encouraging diverse and innovative assessment methods beyond traditional exams (Xia et al., 2024). Clear and consistent policies on AI usage are necessary to address issues such as plagiarism, data privacy, and academic integrity, ensuring both students and faculty understand acceptable AI practices (Wu et al., 2024). A holistic approach to policy development can foster an environment that maximizes the potential of GenAI while protecting students' well-being and academic integrity (Perera & Lankathilake, 2023). Comprehensive policy frameworks are essential for guiding the responsible integration of GenAI in education, promoting ethical, sustainable, and balanced practices.

Conclusion

This exploratory study was conducted to gain a deeper understanding of GenAI use and its impact on users in Malaysian university setting. After collecting and analyzing 290 data sets from different users from Malaysian public and private universities, we found that most university user's declared critical insights into the features, motives and benefits that sustain their engagement with AI applications and this provided us answer to RQ1, where standout feature reported by respondents is the GenAI ease of access and use, followed by innovative and novel responses highlighting them as the most two key engagement factor. Additionally, the text generation tools, such as ChatGPT and Gemini, dominate usage among Malaysian university users, with 92.1% of 290 respondents using these applications. Results show that time-saving is the most significant benefit, selected by users followed by problem-solving capabilities as the most two GenAI key benefits. Responding to RQ2 regarding negative impacts associated with use of GenAI applications, majority of respondents express moderate to strong concerns (Agree and Strongly Agree) about these impacts. The most significant concerns are increased stress from dependency on technology (72% agree or strongly agree) and undermining traditional educational methods (55% agree or strongly agree). These findings suggest that while generative AI applications offer benefits, they also pose significant risks to communication skills, academic performance, stress levels, traditional education methods, academic integrity, and motivation.

Responding to RQ3 regarding to what extent are university users intensively using generative AI apps and wither some demographics has any relationship with generative AI over engagement and excessive use among university users, the analyzed results using one way ANOVA revealed that the younger users, particularly those under 25 years old, are more engaged with generative AI applications compared to older users with 0.029 p-value (less than 0.05), therefore the null hypothesis was reject the that age does not impact AI engagement levels. The results of one way ANOVA test showed no significant difference in AI engagement levels between males and females ($F = 1.457$, $p = 0.228$). This suggests that gender does not play a significant role in influencing engagement with generative AI applications among university users. The ANOVA results reveal a significant difference in AI engagement levels based on the level of education ($F = 5.991$, $p = 0.001$). This supports the observation that users with a Bachelor's degree are more engaged compared to those with a Master's degree, PhD holders, and those with other degrees. Surprisingly, the ANOVA results based on duration of AI experience revealed no significant difference in engagement levels ($F = 2.197$, $p = 0.089$). This suggests that the duration of AI experience does not significantly impact engagement levels among university users. The ANOVA results for weekly usage hours show a marginally non-significant difference in AI engagement levels ($F = 2.072$, $p = 0.057$). This suggests that while there is a trend indicating higher engagement with increased weekly usage hours, it is not statistically significant at the 0.05 level.

Finally to answer RQ4, we introduced set of practical guidelines and recommendations to promote healthy AI practice, it integrates key essentials as follow: self-regulation skills, digital detox practices, as an individual level with policy support, training support as organizational and institutional level and AI technology literacy, community engagement as technology and environment level. Together, these guidelines provide a comprehensive practical recommendations that supports students and users in managing AI usage effectively in university settings by fostering a balanced approach that enhances their academic performance, mental health, and ethical awareness in the digital age.

Research Implications

The findings of this research have significant implications for the integration and management of generative AI applications in educational settings, particularly within Malaysian universities. Firstly, the high engagement of younger users with AI tools suggests that universities should capitalize on this trend by embedding AI technologies into curricula and learning processes. This can enhance educational experiences and outcomes by leveraging the time-saving and problem-solving capabilities of AI. Additionally, the widespread use of AI for educational purposes underscores the need for institutions to provide adequate support and resources, ensuring that both students and staff are well-equipped to utilize these technologies effectively. Furthermore, the identification of key negative impacts, such as increased stress from dependency on technology and the undermining of traditional educational methods, calls for a balanced approach to AI integration. Universities should implement strategies that mitigate these risks, such as promoting digital detox practices and encouraging self-regulation among users. This approach can help in maintaining mental health and preserving the integrity of traditional educational methodologies.

The gender-neutral findings in AI engagement indicate that AI adoption strategies can be uniformly applied across male and female users, focusing more on the level of education and specific user needs rather than gender-based preferences. On the other hand, the higher engagement levels among users with a Bachelor's degree compared to those with higher degrees suggest that educational programs at the undergraduate level might benefit the most from AI integration, potentially driving higher adoption rates and more innovative uses of AI in research and learning. Lastly, the research highlights the importance of developing comprehensive guidelines and recommendations to foster sustainable AI practices. These guidelines should include policy frameworks, training programs, and initiatives that promote AI literacy and community engagement. By doing so, universities can not only enhance academic performance and productivity but also ensure that AI usage aligns with ethical standards and supports the overall well-being of students and staff. Future research should continue to explore these dynamics, offering deeper insights into how AI can be harnessed to support educational excellence while mitigating its potential downsides.

Research Limitations and Future Directions

Firstly, the sample size and diversity of this study are limited. Although 290 respondents provide a sufficient basis for initial insights, this sample may not fully capture the diverse demographics of university users across Malaysia. Future studies should aim to expand the sample size and diversity by including a larger and more varied sample of respondents from different regions and educational institutions. This will enhance the representativeness and generalizability of the findings.

Secondly, the study's geographic limitation to Malaysian universities restricts the applicability of the findings to other regions. Educational systems, technological advancements, and cultural attitudes towards AI vary globally, influencing AI engagement and its impacts differently. Comparative studies across different countries and regions are recommended to provide insights into these variations and help identify best practices and unique challenges.

Thirdly, the reliance on self-reported data introduces potential biases, such as social desirability and recall biases. Respondents may inaccurately report their engagement levels and perceptions of AI impacts, skewing the results. Incorporating in-depth qualitative research methods, such as interviews and focus groups, can offer richer, more nuanced insights into the motivations, experiences, and perceptions of university users regarding generative AI. This qualitative data can complement quantitative findings for a more holistic understanding of AI engagement.

Fourthly, the cross-sectional design of this study captures data at a single point in time, limiting the ability to infer causal relationships between demographic factors and AI engagement levels. Longitudinal studies should be implemented to track the evolution of AI usage patterns and impacts over time. This approach can establish causal relationships and provide a deeper understanding of the long-term effects of AI engagement on academic performance, mental health, and other outcomes.

Fifthly, this research focus on specific generative AI tools, such as ChatGPT and Gemini, may not represent the full spectrum of AI applications used in educational settings. Including a broader range of AI tools in future research can provide a more comprehensive understanding of AI engagement and impacts. Investigating the usage and impact of AI in areas such as virtual teaching assistants, adaptive learning systems, and AI-driven research tools can offer a broader perspective on AI's role in education. Finally, as AI technology continues to evolve, future research should address new developments and their implications for education. Investigating ethical considerations and potential risks associated with emerging AI technologies will be crucial for developing responsible and sustainable AI practices. By addressing these research limitations and pursuing these directions, future studies can contribute to a more comprehensive and nuanced understanding of generative AI usage in university settings, ultimately supporting the development of effective strategies to enhance its benefits while mitigating its risks.

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