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AI Usage and Students' Academic Performance: BA Major Students' Perspective

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A B S T R A C T

This study investigates the impact of Artificial Intelligence (AI) usage on the learning experiences of Hanoi students, focusing on their perceptions of AI accessibility and how their habits in using AI affect their academic performance, learning efficiency, and motivation. Integrating AI into education allows students to apply theoretical knowledge and skills practically, exposing them to advanced learning methods and creating a conducive environment for knowledge acquisition. This technological integration benefits not only students but also teachers, enabling them to seamlessly incorporate information into classroom lessons using AI applications. Data was collected from 400 university students majoring in Business Administration in Hanoi, and this study used in-depth interview with experts to develop measurement tools. The study assessed students' views on teachers' teaching methods and the combined use of technology with self-study. Using econometrics software, the study applied rigorous criteria to test the reliability and confirm the measurement variables, ultimately presenting the results and conclusions of the research objectives.

Keywords: Education, AI Usage, Students' Academic Performance, Students' Learning Motivation, SEM.

1. Introduction

In the context of rapid global advancement, technology is increasingly utilized across a range of sectors, including agriculture, industry, services, and notably, education. Niess (2005) highlights substantial progress in educational technology integration over the past decade. Research by Kay (2004), involving teachers provided with computers and related technologies, found that such integration led to improvements in students' learning attitudes and motivation. These positive results necessitated significant adaptation by educators, who faced a demanding and protracted process to incorporate new technologies into their instruction (Ertmer & Ottenbreit-Lefwich, 2010). Koehler and Mishra (2009) emphasize that technology integration in teaching remains complex, presenting ongoing challenges for practitioners. Nevertheless, Lawless and James (2007) observed that technological proficiency has become essential for modern educators, and the increasing prevalence of electronic resources in educational settings requires teachers to adopt technology effectively, even though this adoption may proceed more slowly than other instructional activities.

University students encounter technology early through video games and various media. Katz (2008) notes that the ongoing rivalry between technology and education shapes economic growth and social inequality. Research reveals rural students in middle-income countries have less technology access than their urban peers (Croft et al., 2019). The COVID-19 pandemic accelerated remote learning adoption, with Bates (2005) describing distance education as flexible and technology-driven. E-learning is convenient, cost-effective, and satisfies users (Ruiz et al., 2006), yet pandemic-era studies show rural and low-income youths face internet access gaps (UNICEF, 2020), affecting their academic outcomes. Artificial intelligence has since become a leading educational technology.

Contemporary students increasingly leverage technology, particularly smartphones, as integral tools for learning (Singh & A. Samah, 2018). Functioning as portable computers, smartphones provide constant internet access, facilitating convenient and autonomous study by offering a wide array of information resources. They are widely recognized as effective learning aids. Research demonstrates that while desktop computers are accessible at universities, most students opt to use smartphones for reading materials and information retrieval (Mwalukasa, 2023). This trend underscores the integration of emerging technologies, including artificial intelligence (AI), into higher education environments. Online platforms, internet-based technologies, and social media have transformed communication between faculty and students, enhancing information exchange. Notable advancements include wikis, email, Twitter, and especially AI, which collectively enable greater access to diverse knowledge sources. The introduction of AI, in particular, offers substantial benefits to student learning.

According to K. Ratheeswari (2018), incorporating technology into teaching and training programs enhances instructional quality. The utilization of innovative technologies such as AI fosters an optimal learning environment, stimulating both student engagement and academic achievement. Prior studies generally report positive effects from technology integration (Raja & P.C. Nagasubramani, 2018); however, some literature highlights both beneficial and adverse impacts, with instructors largely indicating that technological support varies by discipline and tends to increase student motivation

(Carstens et al., 2021). Additional research notes that, while technology positively influences educational outcomes, it can also introduce challenges (Walia et al., 2021). Therefore, although technology and AI deliver significant advantages and support student learning, they may also present potential drawbacks.

Empirical evidence reveals both positive and negative effects of AI on student academic performance. Technology is a valuable educational tool, but its efficacy depends on proper and judicious application. Current research emphasizes the necessity of integrating technological skills within teaching and learning processes to ensure students remain adept in an evolving digital landscape (Strom, 2021). Today's technological ecosystem comprises numerous resources that impact student motivation; different tools may either reinforce or impede foundational skills acquisition. As the primary objective of education is to nurture learning motivation, technology plays a critical role in achieving this aim (Flanagan & Jennifer Lyn, 2008). Further studies suggest a bidirectional relationship between technology usage and academic performance - overall correlations tend to be negative though not statistically significant, yet certain forms of technology, such as social media, show notable positive associations (Rashid & Asghar, 2016).

The prevalence of social media use among young people, accessed predominantly via smartphones, has been found to enhance students' capacity for information acquisition, yielding both positive and negative consequences (Raut & Patil, 2016). Participation in social media supports continual knowledge updates through subject-specific groups and broadly shared online content. Reading remains crucial for individual development; Li-Bi Shen (2006) observed that new technologies influence campus-based learning and reading behaviors, with students more frequently engaging with digital rather than printed content. Gender differences also emerge in the effects of technology on learning experiences. Overreliance on technology can result in distractions and a diminished capacity for independent thought. Excessive use, particularly among youth, may foster problematic behaviors such as gaming addiction, negatively impacting academic outcomes by reducing study time (Gómez et al., 2020). While technology creates a familiar environment conducive to information access, concerns remain regarding the proliferation of inaccurate or misleading content. Esteban Vázquez-Cano et al. (2022) highlight the difficulty students face in discerning credible information amidst abundant sources, which is a key challenge in the effective use of AI. Acceptance of false information can adversely affect academic progress and influence day-to-day interactions.

Despite these challenges, AI exerts a generally positive effect on learning environments, enriching educational experiences through digital engagement (LN Rufaidah et al., 2021). Additional research indicates that technology can effectively motivate learners (Granito & Chernobilsky, 2012; Harandi, 2015), with overall positive associations on academic performance (ISTE, 2002), notwithstanding potential negative implications. Based on theoretical and empirical literature, the present study examines determinants of AI adoption as an emergent technology, investigating its direct and indirect effects on student learning within educational contexts and presenting statistical analyses and conclusions regarding technology's impact on student achievement.

2. Research Model & Hypotheses

Drawing upon established theoretical frameworks and previous research, this study outlines a focused direction examining students' access to artificial intelligence (AI), their competence in utilizing AI, and patterns of AI usage, all of which have implications for learning outcomes. Furthermore, as previously discussed, AI influences various aspects of education, including its impact on educators themselves. The investigation will assess teachers' proficiency with AI and evaluate the extent to which it affects student achievement. Accordingly, the following research model and hypotheses are presented:

H1: AI accessibility impacts students' academic performance

H2: AI proficiency impacts students' academic performance

H3: Teachers' AI proficiency impacts students' academic performance

H4: AI usage habits impact students' academic performance

H1 seeks to establish that students' access to artificial intelligence directly affects their learning outcomes. Evidence suggests that the majority of young individuals are introduced to AI early in life, reflecting a generally high level of technological access among students. Nonetheless, significant disparities exist, as some students experience restricted access to technology. This discrepancy forms the foundation of the first hypothesis.

Previous research indicates widespread early exposure to technology among students, raising questions about their methods of acquiring AI proficiency and relative skill levels. For this study, AI proficiency is defined by students' interactions with AI—specifically, whether they encounter difficulties when utilizing this technology for particular tasks and whether students with varying degrees of accessibility (H1) find AI use more or less challenging. Furthermore, literature reviewed has identified another relevant factor: students' patterns of AI usage. These studies show that non-academic habits, such as dependence on AI, frequently develop. Such findings informed the formulation of hypotheses H2 and H4.

Hypothesis H3 emerged from an examination of the broader educational context, particularly the influence that AI has on both education and educators. The pedagogical strategies and technological tools adopted by teachers play a crucial role in shaping student learning experiences through their impact on content delivery.

This research adopts a quantitative methodology, employing survey instruments to gather data. The approach involves collecting and analyzing quantitative data to investigate the relationships between variables. The primary aim is to gain deeper insights into AI usage behaviors and their influence on student learning within Hanoi. By referencing works such as Sondakh et al. (2023) and Willem E. Saris & Irmtraud N. Gallhofer (2014), the researchers justify the use of questionnaires as their principal data collection method, citing benefits such as ease of access, high reliability, and low operational costs.

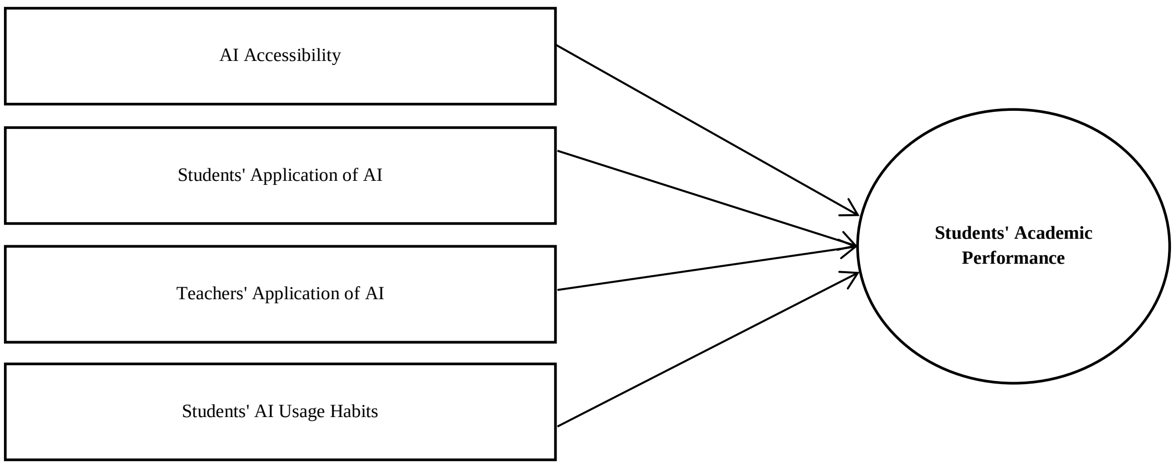

Fig. 1 - Proposed Research Model

3. Results and Discussion

3.1. Sample

This research study examines the influence of artificial intelligence on academic performance among students majoring in Business Administration at universities in Hanoi. The author utilized a survey methodology, gathering data from 400 participants through a questionnaire distributed via Google Forms. The primary aims included evaluating the reliability and validity of the measurement scale, assessing its effectiveness, and confirming the proposed model. Although 400 valid responses were obtained, the observations are generally considered insufficiently structured due to the non-probability sampling method employed. Consequently, potential biases exist in the regression analysis, and only standardized coefficients following robust modeling are reported.

3.2. Descriptive Statistics

Table 1 presents demographic information regarding the respondents. With respect to gender, a 2% difference indicates that the data is relatively well-structured, with a female proportion of 10.32%. The age distribution demonstrates a non-normal pattern, primarily attributable to convenience sampling and constraints such as limited financial resources. The majority of respondents (91%) are aged between 18 or under and 20 years, comprising mostly freshmen and sophomores, while only a small proportion are third-year students. Additionally, 9% of participants are 21 years or older, representing third- and fourth-year students in most Vietnamese higher education programs; specialized programs, such as those in medicine, may require six years of formal education and training. Approximately 40% of students were born and raised in Hanoi, while the remaining 60% relocated from other cities for their studies, reflecting the broader composition of the student population. Regarding household income, the majority of surveyed students originate from middle-class families: 45.25% from low-middle class and 33% from high-middle class backgrounds. Only 12% and 9.75% of respondents come from low- and high-income families, respectively.

Table 1 - Demographic statistics

Demographic characteristics		Number	Percentage (%)
Gender	Male	204	51
	Female	196	49
Age	18 or under	184	46
	19 - 20	180	45
	21 - 22	28	7
	23 or older	8	2
Hometown	Hanoi	157	39.25
	Others	243	60.75
Income	Under 10 million VND	48	12

Demographic characteristics		**Number**	**Percentage (%)**
	10 - 20 million VND	181	45.25
	20 - 30 million VND	132	33
	Above 30 million VND	39	9.75

Table 2 - Descriptive statistics

Variables	**Items**		**Mean**	**Std. Dev.**
AI Accessibility	AA1 - General AI items accessibility		4.20	0.779
	AA2 - Personal AI items accessibility		3.51	1.007
	AA3 - Internet accessibility		3.48	1.178
	AA4 - Academic materials accessibility		3.16	0.814
Students' Application of AI	SAA1 - In-class applications		4.05	0.795
	SAA2 - Outside of class general applications		4.19	0.892
	SAA3 - Outside of class academic applications		3.18	1.189
Teachers' Application of AI	TAA1 - Willingness to apply		3.88	0.996
	TAA2 - AI applications update		3.91	0.780
	TAA3 - In-class applications		4.41	0.626
	TAA4 - Outside of class applications		3.96	1.082
Students' AI Usage Habits	SAUH1 - Frequency of general usage		4.31	0.745
	SAUH2 - Total time of general usage		4.16	0.815
	SAUH3 - Frequency of academic usage		3.39	1.267
	SAUH4 - Total time of academic usage		3.41	1.199
	SAUH5 - AI practice		3.70	1.404
	SAUH6 - AI update		4.09	1.324
Students' Learning Motivation	SLM1 - Amotivation (reversed coding)		3.52	0.841
	SLM2 - Regulated extrinsic motivation		4.45	0.699
	SLM3 - Internalized extrinsic motivation		3.18	0.920
	SLM4 - Intrinsic motivation		3.20	1.017
Perceived Academic Performance	PAP1 - In-class participation		3.57	1.001
	PAP2 - Understanding of in-class materials		3.60	0.922
	PAP3 - Performance self-evaluation		3.85	1.171
	PAP4 - Comparison with other students		3.51	1.065
Variables	**Min**	**Max**	**Mean**	**Std. Dev.**
GPA	1.84	4.00	3.13	0.415

Table 2 presents the descriptive statistics of the principal variables examined in this study. The data indicate that while general access to AI is similar among students, notable differences exist in personal access to AI items. Most students benefit from institutional access through schools, universities, and local communities; however, a substantial proportion also obtains personal access. Internet accessibility is comparable to personal device accessibility, yet the use of online academic materials remains relatively less prevalent. Although students frequently encounter AI applications during class sessions, they are less likely to integrate AI advancements into academic pursuits outside the classroom, with significant variation observed among individuals. With respect to teachers' use of AI, adoption within the classroom is widespread, but there is greater variability regarding their willingness to apply AI, usage outside of instructional settings, and habits of adopting AI updates. Regarding students' AI usage patterns, most are generally engaged with technology, though they demonstrate limited inclination to use AI innovations specifically for academic purposes.

3.3. Measurement overview

Table 3 - Reliability and validity assessment

Variables	**Items**	**Corrected Item - Total Correlation**	**Cronbach's Alpha if Item Deleted**
AI Accessibility Cronbach's Alpha = 0.864	AA1 - General AI items accessibility	0.754	0.776
	AA2 - Personal AI items accessibility	0.638	0.791
	AA3 - Internet accessibility	0.829	0.751
	AA4 - Academic materials accessibility	0.683	0.739
Students' Application of AI Cronbach's Alpha = 0.833	SAA1 - In-class applications	0.655	0.723
	SAA2 - Outside of class general applications	0.654	0.697
	SAA3 - Outside of class academic applications	0.805	0.678
Teachers' Application of AI Cronbach's Alpha = 0.895	TAA1 - Willingness to apply	0.708	0.722
	TAA2 - AI applications update	0.885	0.805
	TAA3 - In-class applications	0.739	0.837
	TAA4 - Outside of class applications	0.777	0.805
Students' AI Usage Habits Cronbach's Alpha = 0.882	SAUH1 - Frequency of general usage	0.844	0.676
	SAUH2 - Total time of general usage	0.821	0.662
	SAUH3 - Frequency of academic usage	0.618	0.655
	SAUH4 - Total time of academic usage	0.890	0.877
	SAUH5 - AI practice	0.636	0.786
	SAUH6 - AI update	0.641	0.736
Students' Learning Motivation Cronbach's Alpha = 0.830	SLM1 - Amotivation (reversed coding)	0.630	0.802
	SLM2 - Regulated extrinsic motivation	0.645	0.791
	SLM3 - Internalized extrinsic motivation	0.679	0.776
	SLM4 - Intrinsic motivation	0.686	0.774
Perceived Academic Performance Cronbach's Alpha = 0.900	PAP1 - In-class participation	0.756	0.669
	PAP2 - Understanding of in-class materials	0.726	0.846
	PAP3 - Performance self-evaluation	0.799	0.826
	PAP4 - Comparison with other students	0.837	0.823

The table above exhibits satisfied coefficients of all variables (four independent, two dependents) with Cronbach's Alpha all above 0.6, and the total correlation coefficients of their corresponding items are all greater than 0.3. Therefore, we proceed to further analysis without elimination of any items. In general, the scales' reliability is validated.

3.4. Results and Discussion

Table 4 - Linear regression results

Variables	**Perceived Academic Performance**					**GPA**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
AI Accessibility (AA)	0.262*	0.157	0.267	0.233*	0.288*	0.238**	0.215*	0.258*	0.224*	0.223**
Students' Application of AI (SAA)	0.414***	0.180***	0.169*	0.119**	0.301**	0.318***	0.336**	0.328**	0.346***	0.354***
Teachers' Application of AI (TAA)	0.189*	0.039	0.178**	0.111	0.205*	0.105*	0.172	0.171*	0.195*	0.192
Students' AI Usage Habits (SAUH)	0.280*	0.219*	0.158*	0.226*	0.220**	0.227***	0.176**	0.248**	0.245**	0.236*
AA*SAA		0.248**					0.281**			
AA*TAA		0.172*					0.231***			
AA*SAUH		0.218***					0.162**			
Gender (Male = 1)			0.054***					0.091***		
Gender*AA			-0.237*					-0.239**		
Gender*SAA			-0.279***					-0.253**		
Gender*SAUH			-0.228***					-0.218***		
Hometown (Hanoi = 1)				0.061					0.051*	
Hometown*SAA				0.247**					0.311***	
Hometown*TAA				0.194***					0.245**	
Hometown*SAUH				0.233***					0.249**	
Income (20 million and above = 1)					0.088*					0.048*
Income*SAA					0.274***					0.318**
Income*TAA					0.251**					0.241*
Income*SAUH					0.181***					0.274**
Adjusted R^2	0.6385	0.7797	0.6184	0.6337	0.6984	0.6821	0.7958	0.7833	0.6252	0.6723
					*	Sig. 10%	**	Sig. 5%	***	Sig. 1%

Table 4 provides a summary of the linear regression analysis results, which investigate the relationship between four independent variables and two dependent variables. The variable representing students' learning motivation (SLM) was excluded due to statistical insignificance across all determinants. Ten models were considered: the first five assess the impact of predictors on students' perceived academic performance, while the remaining five focus on actual academic performance as measured by GPA. Model one serves as the base and incorporates only the four independent variables; model two extends this framework by introducing interaction terms, specifically between AI accessibility and each of the other three variables. The third model further includes gender as a dummy variable and its corresponding interactions, the fourth adds students' hometown, and the fifth introduces household income. Adjusted R^2 values for all models range from 0.6 to 0.8, indicating a strong explanatory power. It should be noted, however, that the sample is limited to freshmen and sophomores in Hanoi, potentially introducing bias toward this demographic.

The findings indicate that all independent variables are statistically significant with positive effects on academic performance in the base models. Notably, AI demonstrates a greater influence on perceived academic performance than on GPA, with the latter exhibiting lower levels of statistical significance—meaning there is a reduced likelihood of incorrectly rejecting the null hypothesis regarding the effect of the explanatories. Additionally, individual student characteristics appear to exert a more substantial impact on academic performance than broader AI factors such as accessibility or teacher usage. A key observation is that general AI condition variables become statistically insignificant in models with interaction terms, suggesting that their importance varies according to specific group characteristics.

From the data presented, it may be concluded that male students marginally outperform female students academically; however, no statistically significant conclusions can be drawn concerning students' hometown or family background (specifically household income). Students with improved AI accessibility tend to achieve better academic outcomes when all other AI-related conditions are comparable, underscoring the relevance of AI access, which becomes more pronounced as both students and teachers integrate AI into educational practices. Gender-based analysis reveals that although male students generally perform slightly better, their performance declines relative to female students when AI is incorporated, likely due to excessive reliance and limited discretion in AI usage. With respect to hometown, students from Hanoi appear to possess notable AI advantages over their peers from other cities. Household income analysis indicates that students from higher-income families demonstrate significantly superior academic performance as AI advancements are increasingly adopted in higher education settings.

4. Conclusion

The research highlights the significant impact of artificial intelligence (AI) on student learning. Findings indicate a complex relationship between AI usage and student outcomes, with predominantly positive effects observed. The data shows that AI meaningfully shapes students' educational experiences in various ways, particularly among male students, those from small towns and cities, and individuals from low-income backgrounds. While AI improves accessibility, engagement, and personalized learning, it also presents challenges, such as potential dependency.

Within the broader educational landscape, the study acknowledges that AI's influence extends to educators as well. Teachers' ability to seamlessly integrate AI into instructional practices is crucial, as innovative, AI-informed methods have the potential to revolutionize pedagogy by making learning more dynamic and adaptive. Nonetheless, students' habits and approaches to using AI, especially in academic contexts, are critical determinants of both perceived and actual academic performance. Students who utilize AI for exploration, collaboration, and self-directed learning tend to demonstrate increased initiative and interest in their studies.

The report recommends that teachers continue to develop their AI-related competencies and instructional strategies, while stakeholders, including students, schools, universities, and local authorities, work collaboratively to equip learners with essential digital skills. This is especially important for students from small towns, cities, and low-income families. In conclusion, this research illuminates the complex dynamics among AI, education, and student learning. By fostering active participation, initiative, and sustained engagement, educators and policymakers can maximize the transformative potential of AI across diverse educational settings.

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