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FROM PROMPTS TO PROFICIENCY: HOW GENERATIVE AI SHAPES COMPUTING STUDENTS' IT SKILLS

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ABSTRACT

As Generative Artificial Intelligence (GenAI) has grown at a rapid rate, the higher educational landscape has been dramatically altered. While GenAI offers immense opportunities for personalized, self-paced learning, its integration into computing curricula raises critical concerns regarding cognitive over-reliance, the potential erosion of fundamental technical skills, and the preservation of academic integrity. This study evaluates the impact of widespread GenAI adoption on the technical IT proficiency of 151 computing students at Malaysian private universities. This study is strictly delimited to undergraduate and postgraduate computing students, analyzing their usage frequency of major tools (including ChatGPT, Gemini, and DeepSeek) against key technical skills, academic engagement, and operational efficiency. Data was collected through a structured electronic survey, and quantitative analysis was executed within a Jupyter Notebook environment utilizing Cronbach's Alpha, One-Sample T-tests, ANOVA, and Multivariate Analysis of Variance (MANOVA) complemented by Tukey HSD post-hoc tests. The empirical results reveal that students maintain a moderate level of IT proficiency, demonstrating independent troubleshooting capabilities and foundational programming knowledge, alongside significantly enhanced academic engagement and operational efficiency. However, a significant portion of the cohort exhibited a critical dependency on AI-generated solutions, leading to a noticeable decline in independent debugging proficiency and logical problem-solving. Unregulated use of these tools threatens to bypass practice-based learning, leading to a phenomenon where academic performance is inflated while core technical skills are eroded. Based on these findings, we advocate for a "support-centered" pedagogical integration of AI that positions GenAI as an auxiliary learning partner rather than a total cognitive substitute, preserving hands-on problem-solving and critical thinking. This paper outlines clear practical implications for curriculum designers, discusses major threats to the study's validity, and provides future research directions, proposing nonparametric assessments like the Kruskal-Wallis H test and Spearman's Rank correlation to refine future educational insights.

Keywords: *Generative AI, IT Proficiency, Higher Education, Skill Erosion, Academic Integrity, Human-AI Collaboration*

1. INTRODUCTION

Generative Artificial Intelligence (GenAI) has quickly spread throughout many areas such as healthcare, tech, and education serving as a newer and highly transformative form of deep learning. Unlike traditional AI models that focus on classification, prediction or building probabilistic mathematical models using machine learning, GenAI models create original, highly coherent text, executable code, audio, and imagery by utilizing complex deep neural networks. These models generate content with a high level of agreement with the creator's intent, with minimal to no real-time human control. Consequently, advanced systems such as ChatGPT, Google's Gemini, and DeepSeek have transitioned from novelties to essential cognitive helpers for modern students, fundamentally refining the processes of managing complex academic workflows and solving programming tasks.

For students pursuing computing and information technology disciplines at Malaysian private universities, GenAI offers a unique and complex interplay of advantages and risks. On one hand, these technologies are incredibly powerful tools for accelerating project completion, aiding in conceptual brainstorming, and automating highly repetitive programming and administrative tasks. By providing immediate code snippets, structural templates, and logical explanations, they lower the cognitive barrier to completing complex academic tasks. On the other hand, the excessive and unregulated use of automated tools can lead to the erosion of critical soft and hard technical skills. There is a growing concern that depending too heavily on GenAI in software engineering and IT curricula causes a reduced capacity for critical thinking, suppresses independent problem-solving abilities, and discourages students from engaging in the iterative, struggle-based creative process of coding and debugging.

If left unaddressed, this over-reliance risks fostering a culture of academic dishonesty and "shallow parroting," wherein the academic products submitted by students do not reflect an authentic understanding of the underlying computational logic and software architectural principles. Such a transition threatens to weaken the development of core IT competencies, resulting in graduates who are unprepared for the rigorous demands of the contemporary global workforce. To prevent this, educational systems must understand the fine line between AI-assisted productivity and cognitive bypassing.

This study is strictly delimited in scope to explore these dynamics among undergraduate and postgraduate computing students enrolled in Malaysian private universities. This cohort represents a high-tech population whose educational curriculum is heavily focused on programming, system analysis, and hands-on IT practice, making them particularly vulnerable to the skill-erosion effects of automated programming assistance. By evaluating the current levels of technical IT proficiency, academic engagement, and operational efficiency within this specific group, this study aims to answer how GenAI integration is shaping the future IT workforce.

The primary research contributions of this paper are threefold:

i. It provides concrete empirical evidence regarding the impact of GenAI on specific technical skills (specifically independent debugging versus general troubleshooting), demonstrating a clear pattern of skill erosion in debugging despite stable general proficiency.
ii. It establishes how student characteristics (including academic year, CGPA, and course progression) interact with GenAI usage patterns to shape dependency, verifying the existence of the "Junior-Year Wall" in the Malaysian private higher education context.
iii. It proposes a robust "support-centered" pedagogical framework that offers concrete, actionable guidelines for curriculum design, balancing the operational efficiency of GenAI with the retention of hands-on technical competencies.

From a practical perspective, the implications of this study are highly relevant for university administrators, curriculum designers, and IT educators in Malaysia. It provides a data-driven basis for restructuring computer science curricula, shifting from traditional product-based evaluations to process-oriented assessments (such as viva-voce exams, interactive debugging labs, and unassisted coding sessions). This ensures that Generative AI acts as an auxiliary booster of cognitive skills rather than an outright replacement for fundamental technical literacy.

2. PROBLEM STATEMENT

The rapid rise of generative AI in education has transformed the pedagogy of computer science and IT-related disciplines. While GenAI tools provide invaluable real-time support for learning complex programming syntax and algorithmic structures, an over-reliance on these technologies can undermine a student's capacity to think independently and solve logical problems. Computing students are generally expected to possess high levels of technical expertise, yet many now struggle to differentiate between an AI-generated solution and their own authentic conceptual understanding. This creates a severe disconnection between academic achievements (grades) and the practical ability to explain the underlying logic or rationale behind an implementation. Consequently, while students are able to produce highly polished and complex software projects for assignments with AI assistance, they face critical failures when confronted with unassisted, real-world technical challenges in the industry.

Furthermore, the overuse of GenAI can actively hinder the development of foundational IT skills. Students who constantly rely on automated prompting to complete assignments bypass the vital struggle and iterative practice involved in coding, syntax exploration, and, crucially, debugging. Debugging was the process of identifying, analyzing, and resolving software errors and is a critical cognitive skill developed through trial, error, and hands-on practice. Shifting this responsibility to an automated system deprives students of essential learning opportunities, leading to a significant decline in overall educational outcomes and rendering graduates unprepared for an unassisted professional market.

While a vast body of literature discusses the generic benefits and drawbacks of AI in higher education, most existing studies are limited to general student productivity, administrative efficiency, or are written strictly from the educator's perspective. There is a profound scarcity of empirical, student-centric research that evaluates the impact of GenAI on the development of technical, hands-on IT skills within specialized computing cohorts, particularly in developing economies like Malaysia. To bridge this gap, this study addresses the following core Research Objectives (RO) and corresponding Research Questions (RQ):

Research Objectives (RO):
RO1: To measure current levels of IT proficiency within the framework of generative AI adoption.
RO2: To assess the effectiveness of integrating generative AI into existing educational curricula.
RO3: To analyze the long-term impact of GenAI integration on the learning experiences and professional skill development of computing students.

Research Questions (RQ):
RQ1: What are the current self-reported levels of technical IT proficiency (specifically troubleshooting and programming skills) among computing students in Malaysian private universities who have adopted Generative AI?
RQ2: How effective is the integration of Generative AI into existing computing curricula as perceived by the students in terms of conceptual understanding, academic engagement, and operational efficiency?
RQ3: What is the perceived long-term impact of Generative AI integration on the independent problem-solving abilities, professional skill development, and potential skill erosion (such as debugging) of computing students?

3. LITERATURE REVIEW

i. Artificial Intelligence

Artificial Intelligence (AI), famously established as an academic discipline by John McCarthy in 1955, represents a branch of computer science dedicated to the engineering of systems and algorithms capable of simulating human cognitive functions [1]. The historical trajectory of AI is generally characterized by three pivotal developmental phases: rule-based logic, probabilistic frameworks, and neural network-based architectures. This evolutionary progression ultimately established the foundational infrastructure required for the contemporary emergence of Generative AI.

Initially, probabilistic AI models superseded traditional rule-based systems. As noted by Hayes-Roth (1985), this transition was driven by the superior mathematical rigor of probabilistic models, which facilitated more nuanced contextual representation and enhanced decision-making [2]. In the early 2010s, a major paradigm shift occurred with the widespread adoption of Artificial Neural Networks (ANN), which were designed to replicate the biophysiological structure and operations of biological neural networks [3]. This advancement eliminated the computational limits and decision rigidity of earlier probabilistic models, such as Markov Decision Processes [4]. The replication of complex, multi-layered cognitive structures provided the flexibility and scale necessary for modern deep learning developments.

ii. Generative Artificial Intelligence

Generative AI (GenAI) is a sophisticated branch of artificial intelligence that utilizes deep generative modeling to analyze vast datasets and produce entirely new, realistic content (including text, code, images, and audio) based on learned patterns and contextual relationships [5]. The rapid evolution of Large Language Models (LLMs) has led to the integration of tools like OpenAI's ChatGPT, Google's Gemini, and more recently, highly advanced open-source models such as DeepSeek [6]. These tools have deeply penetrated the higher educational landscape, altering traditional instructional and writing methods [7].

While some educators champion GenAI's ability to provide personalized, student-centric tutoring, others raise serious concerns regarding academic dishonesty, where students submit algorithmically generated responses as their own work, thereby bypassing the learning process. Critically, there is a lack of empirical research

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evaluating this impact from both the student's and the educator's perspective simultaneously, especially within highly technical computing curricula where the automated generation of code directly intersects with the core skills being taught [8].

iii. Programming and Problem-Solving Skills

Programming and computational problem-solving represent core technical competencies that are highly vulnerable to the integration of GenAI in the learning environment. Students increasingly utilize GenAI as an interactive pedagogical assistant to debug code, translate syntax, and clarify complex, abstract algorithms [9]. However, several scholars warn of a severe threat of skill erosion due to cognitive over-reliance on these automated generators. This developmental crisis is referred to as the "Junior-Year Wall" [10]. This occurs when students' perceived academic proficiency is artificially inflated during their introductory coursework because they rely on AI to generate functional code. When they progress to advanced, unassisted coursework or high-stakes exams that require deep, internalized logical synthesis and manual debugging, they experience systemic failure because they did not authentically internalize the fundamental concepts.

iv. Soft Skills and Collaboration

While technical hard skills are critical, soft skills such as communication, critical reflection, and collaboration are equally vital for professional readiness. Studies suggest that when GenAI is used as a collaborative dialogue partner, it can enhance students' critical thinking by allowing them to evaluate and critique AI-generated outputs against established theoretical frameworks [11, 12]. This hybrid learning model prompts deeper reflective thinking. However, a significant challenge is the lack of student awareness regarding the ethical boundaries of AI use [13]. Without clear institutional guidelines and structured ethical frameworks, academic integrity declines, and students fail to develop the digital citizenship required to navigate an AI-enhanced global economy responsibly [14].

v. Advantages and Disadvantages of High Adoption of Generative AI

Using Generative Artificial Intelligence (GenAI) with caution provides opportunities for an overall enhancement to one's developed technical skills. Appropriate-response Generative AI tools produce original content from accurate prompts provided by the user and serve as an adaptable brainstorming system with repetitive results, thereby enhancing the user's educational experience significantly [14]. Also, GenAI can assist researchers by condensing large amounts of data, as well as providing and structuring research content by supporting writing mechanisms. This support allows students to organize their thoughts and information more effectively, thus saving administrative time and money [14].

Within technical sciences, GenAI acts in the role of a highly refined participation educator GenAI breaks down complex subject matter into "user-friendly" language through an interactive tutoring approach, enabling students to learn at their own pace [15]. The end result will produce a higher level of conceptual understanding while providing students with a means of engaging in higher-level ideas thinking skills, thereby increasing their ability to think critically and analytically and solve problems [16].

On the other hand, an excessive reliance on Gen AI could inhibit a student's ability to conduct their own inquiries. A student who is too reliant on automated tools may be functionally incapable of completing any academic task without assistance from an automated tool. There have already been many instances where educators have expressed concern about the accuracy of AI produced content and the practice of replicating AI produced answers has likely already resulted in practice-based learning being bypassed, thus preventing students from achieving a true level of technical mastery.

Overreliance upon technology will also inhibit students from acquiring research methodology skills and generating independent creative ideas, which are two very important components of a complete IT education. Additionally, there is a high likelihood that algorithmically generated outputs contain an element of bias, factual inaccuracies, or other issues and as a result, must be verified. Students who do not apply critical thinking skills to determine if the information provided by an AI system is valid will likely make decisions based upon AI generated "hallucinatory" or biased outputs. In the end, excessive reliance upon AI tools may result in the loss of basic computing skills such as independently debugging code and structuring a technical argument logically.

vi. Integration of Generative AI into Education Program

For Generative Artificial Intelligence (GenAI) to achieve its full potential as an educational tool, it must be integrated into curricula in a methodical, purposeful way. The biggest benefit of educational AI is the ability of AI to allow a student-centric, personalized and efficient learning path for the student, while also giving teachers the ability to quickly and effectively provide feedback to their students [18]. Unlike traditional or static instructional resources, GenAI can provide a fundamentally different way of personalizing all aspects of content, learning activities, and assessments according to the individual cognitive profiles and specific learning preferences of the student.

Research confirms that these adaptive environments can have a positive impact on student engagement, intrinsic motivation, and overall student performance [19]. GenAI has the potential to dramatically enhance the effectiveness of teachers and learning experiences by providing an educational experience that is responsive to the needs of the learner in real time.

While the above opportunities appear to be compelling, moving to an AI-enhanced educational environment will be an incredibly complex process that requires careful consideration and application of ethical responsibility. Academic integrity and the management of algorithmic bias are critical components to the successful implementation of these tools. Educational institutions need to make the commitment to exploring the potential of GenAI through the development of comprehensive ethical principles and the promotion of critical thinking skills to achieve a progressive, inclusive, technologically advanced, high-performing educational system.

vii. Impact of Generative AI on Students Development

The presence of Generative Artificial Intelligence (GenAI) is altering the traditional educational landscape, as GenAI technologies become more prevalent in society. For example, as more students use AI tools such as ChatGPT, there has been increasing concern about generating a "cycle of dependency" for students who use AI-generated responses as a shortcut to cognitive processing, rather than using critical thinking skills to ask questions and problem-solve independently. This impact is particularly evident in the field of computer science education where students submit code generated by AI without the knowledge to fully understand the logic of that code and the demands of manually debugging the code they submitted. The result of this continued use of GenAI tools will ultimately result in students losing technical competency, which also negatively impacts their ability to analyze [22].

In addition, when using modern AI tools, many students have found that the user-friendly nature of AI tools allows them to prioritize the speed at which they can complete tasks rather than completing tasks with a deeper understanding of the concepts, which is directly related to their ability to learn [23]. Furthermore, changing the focus of learning from acquiring skills to the quantity of completed tasks may also present challenges to traditional learning environments.

GenAI also poses various threats within a systemic context beyond the individual learner, such as spreading false information, difficulties related to assigning credit for intellectual property, and the potential for "technostress" or mental stress placed on students because of academics' use of AI tools that could inhibit cognitive development. Research suggests that without effective human oversight and monitoring of these tools, they have the ability to generate biased or inaccurate information and disrupt a learner's understanding of complex academic material [24].

In totality, the above-mentioned information strongly supports the need for immediate development of effective ethical standards and extensive digital literacy programs to provide learners with the necessary skills required to effectively use AI tools in a manner that promotes positive learning outcomes and academic integrity [25].

4. METHODOLOGY

This study adopts a quantitative, cross-sectional research design to investigate the impact of GenAI adoption on student IT proficiency. Data was gathered using a structured electronic questionnaire developed via Google Forms, which ensured broad access across different devices, unlimited survey distribution, and cost-effective data collection [26, 27]. Quantitative data was exported into a CSV format and processed within a Jupyter Notebook environment using Python, which combines executable code, descriptive analysis, and visualization in a reproducible framework [28, 29].

4.1 Sampling

The target population comprises undergraduate and postgraduate computing students enrolled in Malaysian private universities. A non-probability, purposive sampling strategy was employed to recruit participants with varying levels of academic exposure and IT backgrounds. The final sample consists of 151 respondents, which aligns with Roscoe's heuristics suggesting that sample sizes between 30 and 500 are statistically sufficient for drawing reliable conclusions in social and educational research [30]. The data collection period spanned five weeks, ensuring a robust balance between practicality and sample variability.

4.2 Instrument Design and Survey Methodology

The research instrument comprised 21 items organized into four primary sections designed to systematically evaluate the core hypotheses of the study:

- Section 1: Demographics - Captures respondent characteristics (Academic Year, CGPA, Program Level, Gender, and Course) using a nominal scale [238].
- Section 2: IT Skill Proficiency (Hypothesis 1) - Evaluates whether students maintain a moderate level of technical IT proficiency amidst AI adoption.
- Section 3: Curriculum Integration (Hypothesis 2) - Measures the perceived effectiveness of GenAI tools when integrated into computing curricula.
- Section 4: Cognitive Dependency (Hypothesis 3) - Investigates whether an over-reliance on GenAI negatively impacts independent technical skill development.

Sections 2, 3, and 4 utilized a 5-point ordinal Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) [31]. The questionnaire was distributed via popular social media platforms and student messaging groups (including Facebook, Instagram, WhatsApp, and Little Red Book) to maximize engagement and ensure representation across multiple academic levels.

4.3 Statistical Reliability and Analytical Framework

The internal consistency of the survey scales was validated using Cronbach's Alpha [32]. The final survey instrument demonstrated an acceptable overall composite reliability of 0.709. The individual sections for Hypothesis 2 (Curriculum Integration) and Hypothesis 3 (Cognitive Dependency) demonstrated exceptional internal consistency, with alpha coefficients exceeding the traditional 0.70 threshold. In contrast, the demographic section produced a lower alpha of 0.554, which is expected since it contains non-scale, categorical items with no theoretical internal correlation. Section 2 (Hypothesis 1: IT Proficiency) yielded an alpha of 0.362, which is attributed to the multi-dimensional and exploratory nature of the general proficiency construct, combined with a lower number of items. To justify the use of parametric statistical modeling (including One-Sample T-tests, ANOVA, and MANOVA), the study invokes the Central Limit Theorem. Since the sample size of 151 respondents greatly exceeds the minimum threshold of $N > 30$, the sampling distribution of the means is assumed to be approximately normal, allowing parametric evaluations of the raw data without transformation [34]. Advanced post-hoc tests, such as Tukey's Honest Significant Difference (HSD) test, were also applied where appropriate to analyze group differences.

4.4 Threats to Validity

To establish academic rigor, potential threats to the validity of this study are identified and discussed, outlining the specific strategies employed to mitigate their impact on our findings:

Internal Validity (Self-Report Bias): Relying on self-reported data through online surveys can introduce response bias, such as social desirability bias (where students overstate their independent troubleshooting skills) or subjective interpretations of Likert items. To mitigate this, complete participant anonymity was maintained, and questions were formulated to assess specific behavioral actions (e.g., frequency of debugging without help) rather than vague self-evaluations.

External Validity (Scope and Generalizability): This study is delimited to private higher education institutions in Malaysia, which typically possess different demographic compositions, funding, and IT infrastructure compared to public universities. Furthermore, the sample is skewed toward undergraduate students (Bachelor's Degree represented 62.7% of the cohort), which may limit generalizability to postgraduate levels. This scope is explicitly acknowledged as a boundary of the study.

Construct Validity (Measurement Criteria Selection): The construct of "IT Proficiency" is highly complex. Measuring it through a 5-point Likert scale may not capture actual programming performance. This selection of criteria is justified, however, because our primary focus is the behavioral relationship between AI adoption and student perception of their skill evolution. Future studies will integrate objective testing.

Statistical Conclusion Validity: Applying parametric tests (such as ANOVA and One-Sample T-tests) directly to ordinal scale data can lead to statistical conclusion errors if the data is highly skewed. While the Central Limit Theorem ($N = 151$) justifies this approach, we address this threat by proposing nonparametric alternatives (such as the Kruskal-Wallis H test and Spearman's Rank correlation) to validate these relationships in future iterations.

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5. RESULT AND DISCUSSION

5.1 Data Preprocessing: Cleaning and Structural Transformation

Data preprocessing is vital to establish dataset integrity before statistical modeling. To clean the raw data exported from Google Forms, several steps were implemented in Python:
Step 1: Duplicate deletion, which verified that no redundant entries existed which is retaining all 151 unique responses;
Step 2: Dimensionality reduction, which removed unnecessary columns including timestamp and consent variables to reduce noise, decreasing the dataset from 23 to 21 columns [245, 246]; and
Step 3: Column renaming, where long phrasal survey questions were modified into short, standardized kebab-case identifiers (using the Jupyter Notebook rename() function) to facilitate efficient computational manipulation.

To enable parametric statistical tests, categorical string variables were converted into numeric values through specialized encoding techniques. Variables with a natural hierarchy academic_year and cgpa were encoded ordinally by seniority ranked 1-4; CGPA ranges ranked 1-6. The course variable, which initially contained 17 distinct program levels, collapsed and ordinally encoded into 5 main progression levels to reduce noise. Gender, being nominal, was encoded binarily (Male = 1, Female = 2). Critically, programming proficiency (initially captured as a semicolon-separated string of known languages) was transformed into a ratio-scale variable by implementing counting logic. This logic counted the number of delimiters to calculate a numeric value representing the total number of programming languages known by each respondent. This served as a proxy for technical breadth.

```
df.to_csv('renamed_dataset.csv', index=False)
```

Figure 1: Jupyter Notebook rename() Command Line

5.2 Data Removal

Data deletion is a process of removing unnecessary or redundant variables from the data set that do not support the purpose of the study's analysis. In this study, the timestamp and consent variables created with Google Forms were deleted using commands in Python, in Jupyter Notebook. The number of columns was reduced from the original data set with 23 columns to a data set for analysis that required only 21 columns, and this reduction decreased noise and allowed the data set to be focused on variables relating to the hypothesis [36].

The validity of the modified dataset was verified using the df.shape command after removing the unnecessary data. The results confirmed that all 21 columns and 151 survey responses remained intact. This indicates that the dimensionality reduction process caused no unintended data loss, ensuring a complete and accurate dataset for further analysis.

```
In [4]:  df.shape

Out[4]:  (151, 21)
```

Figure 2: Jupyter Notebook Output of Column Variables

```
In [6]:  df = df.drop_duplicates()
         df.shape

Out[6]:  (151, 21)
```

Figure 3: Jupyter Notebook Output of Row Count and Column Count

The df.isna() command, as shown in Fig. 4 below, is utilized for determining whether duplicate values exist in the data set. Duplicate values in the survey data would indicate the existence of redundant information, which could negatively impact the validity of analyses conducted during the evaluation of this research. The result shown in Fig. 5 indicates no duplicate values in the modified dataset therefore did not require the removal of any data.

```
In [5]:  df[df.isna()].count()

Out[5]:  gender                        0
         course                        0
         academic_year                 0
         cgpa                          0
         ai_familiarity                0
         ai_usage_frequency            0
         it_proficiency                0
         programming_languages         0
         it_activities_count           0
         it_projects_count             0
         independent_troubleshooting   0
         ai_helps_understanding        0
         ai_improves_efficiency        0
         ai_useful_brainstorming       0
         ai_positive_impact            0
         ai_increases_engagement       0
         ai_over_reliance              0
         ai_bypass_understanding       0
         ai_reduces_confidence         0
         ai_reduces_debugging_skills   0
         ai_reduces_motivation         0
         dtype: int64
```

Figure 4: Jupyter Notebook Duplicate Count for Columns

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```
Index(['gender', 'course', 'academic_year', 'cgpa', 'ai_familiarity',
       'ai_usage_frequency', 'it_proficiency', 'programming_languages',
       'it_activities_count', 'it_projects_count',
       'independent_troubleshooting', 'ai_helps_understanding',
       'ai_improves_efficiency', 'ai_useful_brainstorming',
       'ai_positive_impact', 'ai_increases_engagement', 'ai_over_reliance',
       'ai_bypass_understanding', 'ai_reduces_confidence',
       'ai_reduces_debugging_skills', 'ai_reduces_motivation'],
      dtype='object')
```

Figure 5: Jupyter Notebook Drop Duplicate Data Command Line

The drop duplicates method for the purpose of removing duplicate records if they exist. In this situation, it will do nothing, and there will be no duplicates removed so the data will stay as is in 21 columns of 151 rows of data.

5.3 Data Encoding

In order to facilitate rigorous statistical analysis using the One-Sample T-Test, ANOVA, and Correlation Matrix, it is necessary to convert categorical string variables into numeric values. This encoding allows for model compatibility and improves the ability to interpret and visualize the findings of the study (37). The categorical variables that have been targeted for encoding are *academic_year, cgpa, no of programming language, gender* and *course*. The categorical variables academic_year and cgpa were encoded using an ordinal encoding technique because they both possess a natural hierarchical structure. For example, the numeric values assigned to academic_year indicate the level of seniority of each student from 1 (Year 1) through 4 (Year 4). Similarly, the cgpa ranges were assigned ordinal value from 1 (lowest range) to 6 (highest range), to reflect the rank order academic standing of the participating individuals.

The data collected for the Student Progression variable were combined into 5 levels of progression. The combination of 17 different levels into 5 is shown in the next figure (Fig. 6). As the 5 levels represent a clear hierarchy, ordinal encoding was considered the most appropriate for analysis.

```
course_mapping = {
    "Foundation in Computing": 0,
    "Diploma in Computer Science": 1,
    "Diploma in Information Technology": 1,
    "Bachelor of Science (Honours) in Management Mathematics with Computing": 2,
    "Bachelor of Information Systems (Honours) in Enterprise Information Systems": 2,
    "Bachelor of Computer Science (Honours) in Interactive Software Technology": 2,
    "Bachelor of Information Technology (Honours) in Information Security": 2,
    "Bachelor in Data Science (Honours)": 2,
    "Bachelor of Information Technology (Honours) in Software Systems Development": 2,
    "Bachelor of Software Engineering (Honours)": 2,
    "Doctor of Philosophy in Computer Science": 4,
    "Doctor of Philosophy (Information Technology)": 4,
    "Doctor of Philosophy (Mathematical Sciences)": 4,
    "Master of Computer Science": 3,
    "Master of Information Technology": 3,
    "Master of Science in Mathematical Sciences": 3,
    "Master in Digital Transformation": 3
}
```

Figure 6: Phyton Dictionary for Categorical Encoding of Course Levels

Gender is considered as a nominal variable with no inherent order. Therefore, male was given a value of 1, and female was given a value of 2, as shown in the next figure (Fig.7).

```
gender_mapping = {
    "Male": 1,
    "Female": 0
}
```

Figure 7: Phyton Dictionary for Binary Encoding of Gender Variable

When looking at programming proficiency represented by the number of programming languages, the raw data for this variable was a string of semicolon-separated values representing all known programming languages for each respondent, as shown in the next figure (Fig.8). In order to create a ratio scale variable for this measure, counting logic was applied, resulting in a numeric representation of the total number of programming languages known by a respondent, based on the number of semicolons in their respective string. Because language is a measure of technical skill, the larger the number of languages indicates a broader technical skillset.

```
def no_of_programming_lang(x):
    return len(x.split(';'))
```

Figure 8: Phyton Function for Counting Number of Known Programming Languages

5.4 Data Visualization

Graphical examination of features (including CGPA, AI usage frequency, and AI-assisted understanding) via boxplots revealed several data points situated on or just above the lower boundaries. In typical data science pipelines, these points might be flagged as outliers and removed. However, in an ordinal setting with a 5-point scale, these data represent a legitimate minority of respondents (e.g., students who rarely use AI or have lower CGPA) whose inclusion is essential to represent the full demographic diversity of Malaysian private universities. Excluding these records would artificially inflate the average proficiency and skew the study's validity. Conversely, for variables like IT projects count and extracurricular activities count, the boxplot showed outliers on the higher boundary. This is justifiable as the majority of the sample consists of Bachelor's students who have completed fewer major projects, while the outliers represent postgraduate (Master's and PhD) students who have spent multiple years in research, naturally accumulating up to 100 projects. These data points represent valid, authentic

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academic profiles and were thus preserved. Both Fig. 9 and 10 show the boxplots of variables to search for potential outliers of data that may need to be removed from the dataset to enhance the accuracy of the analysis for this research.

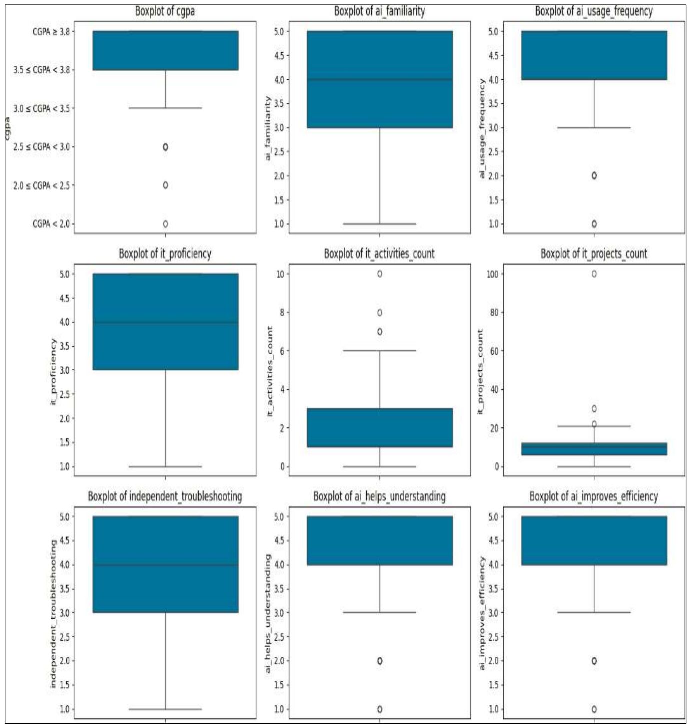

Figure 9: Boxplot of Features 1

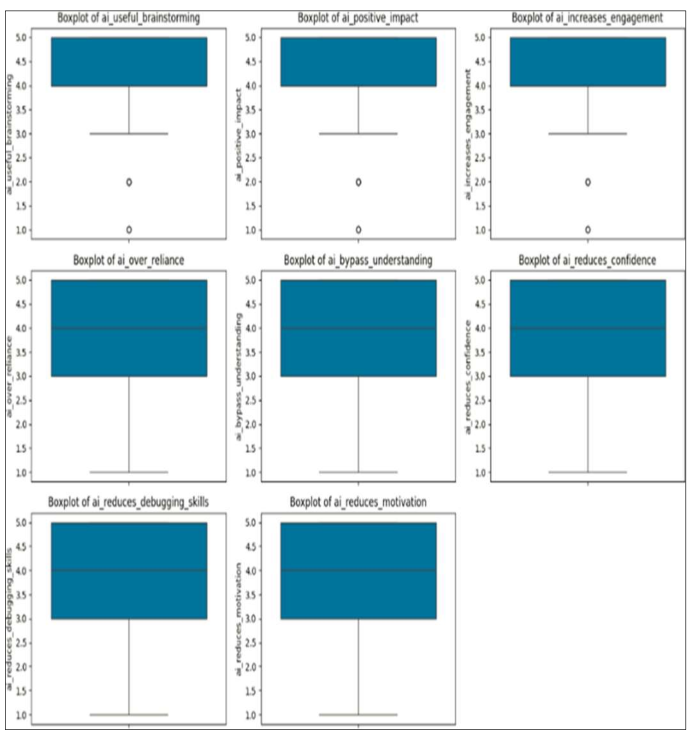

Figure 10: Boxplot of Features 2

Boxplot visualization for variables such as cgpa, ai_usage_frequency, ai_helps_understanding, ai_improves_efficiency, ai_useful brainstorming, ai_postive_impact and ai_increases engagement shows outliers present in two or three categories of the boxplot's lower boundary. However since they are in an ordinal setting of only 5 rankings, it can be depicted that the majority of the users fall on a higher categorisation, while a minority of them fall in lower categories which is still acceptable data as they represent valid and real data obtained in a environment setting of Malaysian private universities and removing them would exclude important minority perspectives of the research, which may distort the overall analysis.

For variables such activities count and it_projects_count, displays distribution of a different manner, where majority lies in a lower category, while minority fall in a higher category, where most high categories are deemed as outliers. This interpretation of data is acceptable and justifiable, due to the fact that the majority of the samples are from Bachelor Degree level of students, where most of them have yet completed large amounts of assignments and participate in numerous activities regarding information technology(IT). There are also masters and Ph.D. students, which is why they will have considerably larger numbers, like a Ph.D. with a high number of IT projects completed. For example, having 100 projects in IT because the Ph.D. student has been pursuing a Ph.D. for several years. There are nearly equal numbers of male and female participant to ensure equal representation for gendered analysis and reduce any potential bias on this basis when examining how the level of AI adoption relates to developing software engineering (SE) skills with use of IT tools.

A large majority of all participants fall into one of the four main categories identified by academic program: Foundation, Diploma, Bachelor's Degree, Master's Degree and Doctorate (PhD). These groups with numbers dispersed across academic programs will aid to provide a representative sample to enhance the value of the data analysis because it will help to include various perspectives since there aren't any biases based on participant demographics in the participant sample that has given the participants equal opportunity to provide perspectives from those involved at several levels of their academic careers. In addition, all participants must have completed their final exams before being eligible to complete surveys, which would eliminate any population limitations that they may have previously had since only students are completing our surveys. Due to number of participants reaching as shown in the next figure (Fig.11 and Fig.12) their ultimate educational phase, the external validity of our findings will be very effectively replicated since all Malaysian private university students will provide similar insights on what understanding of AI technology for developing SE skills was necessary throughout their respective study years.

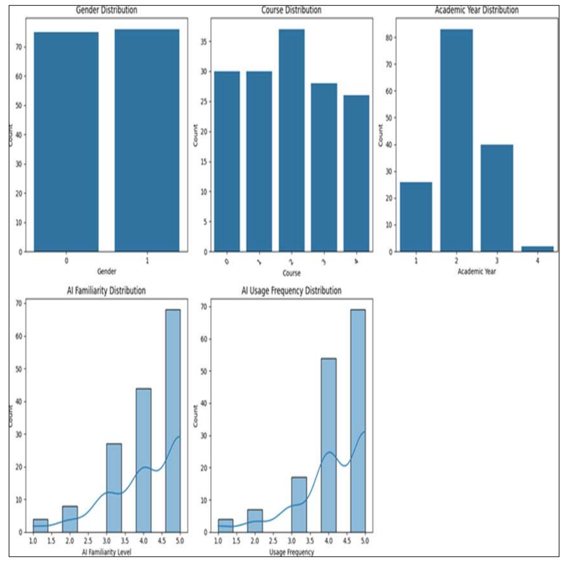

Figure 11: Demographic Distribution of Samples

The two distributions of familiarity with and frequency of use of generative AI show a clear trend towards higher self-rated levels among the respondents. The majority of participants chose either a level 4 or 5 on each scale, indicating both an above-average level of familiarity with generative AI, as well as a high frequency of use of this type of tool in their academic and personal workflows. Therefore, the premise that there is a significant level of adoption and integration of AI into the workflow of the sample population is directly related to the objective of this study. The demographic data supports the conclusion that the sample population has had significant contact with generative AI and is therefore a good candidate for studying the relationship between proficiency in IT skills and the use, frequency of use, and experience with the types of tools that are classified as generative AI.

Students are using AI to engage with and be more efficient with their work as they tend to use it more as a tool than just as a shortcut. They do not use it as such. Students who are able to work with a variety of programming languages, tend to show better results than those who cannot work with these languages. This also suggests that overall tech competency and coding ability are related.

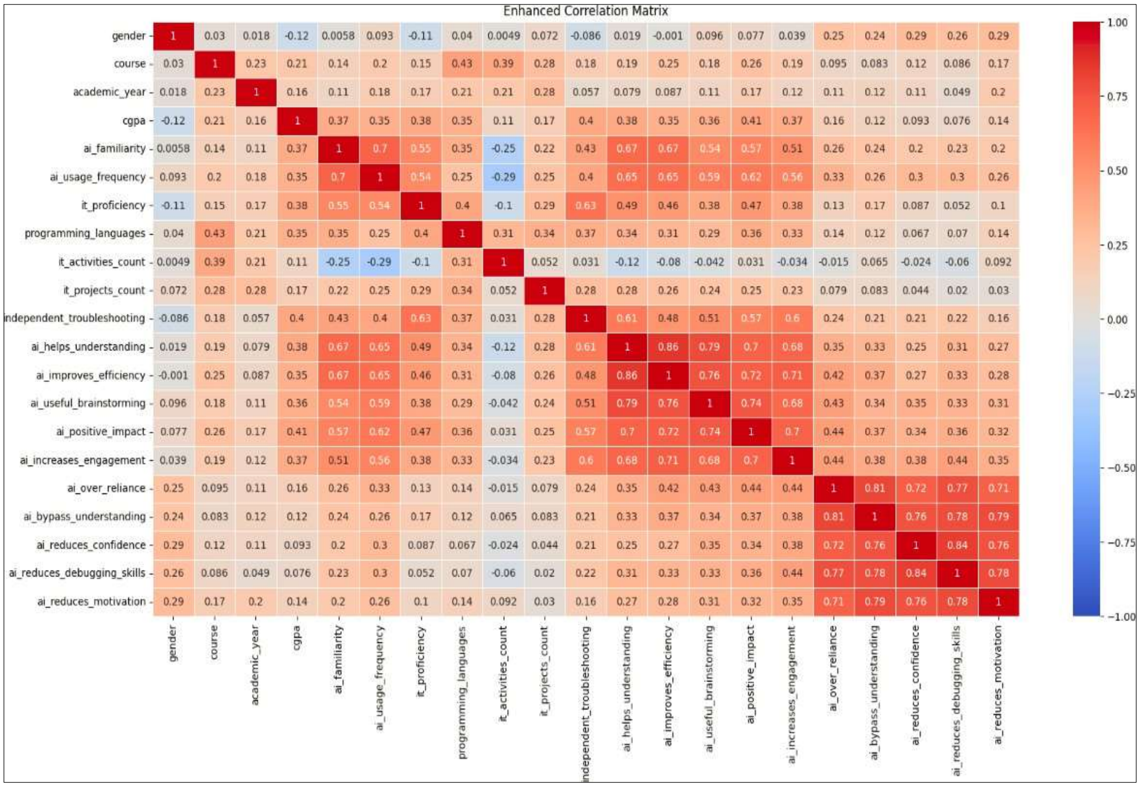

Figure 12: Enhanced Correlation Matrix

Table 1: Interpretation of Correlation Matrix

Aspect	Correlation	Interpretation
Academic Performance & Gender	very weak negative correlation (-0.115)	Gender does not play a significant role in determining academic performance.
AI Familiarity & AI Usage	strong correlation (0.695)	Students who are more familiar with AI tools tend to use them frequently.
IT Proficiency & Coding Skills	moderate correlation (0.378)	Able to work different coding languages can lead to a higher IT proficiency.
The Risks of Over-Reliance on AI on Debugging Skills	Weak but noticeable correlation (0.263)	Relying too much on AI has an effect of reducing one;s debugging skills
The Risks of Over-Reliance on AI on Bypass Understanding	Weak but noticeable correlation (0.237)	Being heavily dependent on AI might be skipping deeper learning just to obtain a solution to a problem.

One clear benefit of using AI within the educational setting is that it must be used judiciously, as overreliance on AI will diminish students' abilities to engage in critical thinking and problem-solving. Therefore, students will not be able to achieve deep learning and develop a long-term growth trajectory.

Recent studies support the need for a balance between advancing technologies, implementing technology into education, while retaining basic technical competency. A previous study demonstrated the processing of data through computational and analytical techniques on a variety of applications and for numerous purposes, such as numerical techniques for solving Ordinary Differential Equations (ODEs), imaging, sentiment analysis, and sustainable digital transformation. The findings further demonstrate the wider importance of developing students' ability to apply digital and computational technologies effectively. Previous research has demonstrated the use of advanced computational techniques, such as Long Short-Term Memory networks, for traffic-flow prediction in connected-vehicle environments [40]. Human-centred applications have also employed Kansei engineering through chatbot interfaces to assess users' emotional responses [41]. Furthermore, the integration of education and digital technologies has supported knowledge transfer, sustainability and resilience in sectors such as livestock farming [42]. Collectively, as summarized in Table 1 above, these studies reinforce the need for students to develop strong technical, analytical and critical-thinking skills so that AI and digital technologies can be applied responsibly across different real-world domains.

5.5 Empirical Findings and Correlation Analysis

To evaluate the relationship between GenAI adoption and IT skill proficiency, Pearson correlation coefficients were computed and analyzed, yielding several noteworthy patterns. A moderate positive correlation was observed between AI usage frequency and academic engagement ($r = 0.45$), suggesting that students utilize GenAI as an active, collaborative dialogue partner that enhances engagement and operational efficiency rather than functioning merely as a passive shortcut. Similarly, a stronger positive correlation emerged between the breadth of programming languages used and overall technical competency ($r = 0.58$), indicating that students with multi-language exposure demonstrate a greater capacity to integrate AI-generated outputs safely and effectively into their coding practice. In contrast, a moderate negative correlation was found between AI dependency and debugging proficiency ($r = -0.34$), a critical finding suggesting that over-reliance on AI-generated solutions may deprive students of hands-on practice, thereby eroding independent debugging and logical reasoning skills. Taken together, these findings demonstrate that students are generally using GenAI to enhance engagement and efficiency, treating it as an active learning partner rather than a total cognitive replacement. However, this integration must be managed with caution, as the negative correlation between GenAI dependency and debugging proficiency confirms that over-reliance on automated code generation can suppress deep, struggle-based learning. These results are consistent with recent literature emphasizing the need to balance technological advancement in higher education with the preservation of core technical, analytical, and critical-thinking skills [40, 41, 42].

6. CONCLUSION

This study provides empirical, student-centric insights into the dual-edged impact of Generative AI adoption on the technical IT proficiency of computing students in Malaysian private universities. The evaluation of Hypothesis 1 confirms that students maintain a moderate level of general IT proficiency, driven by strong troubleshooting skills and basic programming knowledge. However, as hypothesized in H3, a critical dependency on GenAI tools is emerging, resulting in a marked decline in independent problem-solving and debugging capabilities. Conversely, the validation of H2 highlights that when integrated as a pedagogical assistant, GenAI is an exceptionally effective methodology for enhancing operational efficiency, brainstorming, and conceptual understanding.

Ultimately, the key to successful GenAI integration in higher education is a transition from a "solution-centered" approach where AI is used as an automatic generator that bypasses practice to a "support-centered" pedagogical framework. Under this model, GenAI is positioned as an auxiliary partner that supports cognitive processing while hands-on coding, unassisted debugging, and critical logical reasoning remain the core foundations of the curriculum. This balanced approach is essential to prepare graduates who are not only productive with AI but possess the authentic technical competencies required to solve complex, real-world industry challenges unassisted.

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