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Procrastination trap: how personality traits fuel generative artificial intelligence over-reliance and erode academic performance

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ABSTRACT

This study investigates how long-term personality traits contribute to generative artificial intelligence (GenAI) use and whether these traits have an impact on academic procrastination and performance. The Big five personality model was used for this investigation, and a quantitative methodology was employed to analyze data from 200 undergraduate students in East Malaysia via partial least squares structural equation modeling (PLS-SEM). Findings indicated that while neuroticism and openness were associated with increased levels of GenAI use, conscientiousness was found to be a protective factor against GenAI dependency. In addition, results showed that when students excessively utilize GenAI, they experience increased levels of procrastination which leads to longer procrastination periods and decreased levels of deep learning engagement. Finally, procrastination was identified as a partial mediator between GenAI use and poor academic performance. Thus, GenAI dependency produces a 'competence illusion', causing a decline in students' academic abilities over time. Ultimately, this study supports the need for interventions designed to help students learn self-regulation and develop critical AI literacy skills to enable technology to serve as a cognitive scaffold as opposed to a replacement for students' own cognitive efforts.

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1. INTRODUCTION

Generative artificial intelligence (GenAI) is going to be transforming how students learn and the educational environment in much the same way that the Internet did—how GenAI tools (like ChatGPT, Gemini, and Copilot) are being utilized by students. GenAI tools are being used to not only assist students, but as tools to aid in reading summaries, essay writing and completing courseworks [1]. Initial studies suggest that GenAI tools may enhance student productivity and aid students in completing assignments [2]. For this reason, it would be wise for educators to approach GenAI tools with caution. If students continue to rely on GenAI tools, they will not only lose knowledge of what they have learned, but will also relinquish control over their own cognitive processes [3]—term as 'cognitive offloading'—or the tendency for individuals to use technology to avoid thinking [4], [5]. Researchers have found that the utilization of GenAI tools can save students time; however, they have also found that there is a correlation between the use of GenAI tools and lower levels of memory retention, lower levels of creativity and lesser understanding of basic concepts [4].

Indeed, there is nothing novel about a cycle of skepticism towards new technology emerging. Critics were skeptical of the use of handheld calculators in the 1970s and search engines in the 2000s, yet both of these technologies were able to improve the way students learn at a higher level [1]. The GenAI, on the other hand, is different. GenAI is a dynamic, web-based service that cannot easily be restricted. Therefore, instead of simply watching these changes take place, educators will need to adapt the way they assess student knowledge. This is necessary because students commonly use AI tools for assigned tasks, including summarizing readings, clarifying difficult to comprehend concepts, and generating research proposals [6]. Advocates of GenAI view this as an opportunity to customize the learning process; however, the loss of proficiency in fundamental skills by using GenAI is inevitable. These challenges illustrate how quickly the student utilization of GenAI has surpassed institutional regulatory capabilities.

The educational implications of this study are based on the risk of 'cognitive atrophy', which occurs when students go from using GenAI to help them with their studies, to profusely using GenAI as their major thinking mechanism [5]. As long as the underlying psychological precursors—specifically the personality dimensions of Neuroticism and Conscientiousness—are left unaddressed, institutional efforts to design AI policies will be limited to technological restrictions, and therefore unable to address the true cause of the decline in learning [3]. Understanding the psychological factors leading to GenAI dependency will enable educators to develop effective countermeasures to combat AI-based procrastination. AI procrastination does more than merely delay completing tasks; it changes how a student views motivation by choosing instant, but shallow satisfaction from an automatic response instead of the longer term development of mental ability that comes from persevering intellectually [6]. Therefore, this study provides the data needed to develop psychologically informed and targeted strategies that protect genuine academic achievement in an increasingly mechanized educational environment [7].

The need to expedite research on GenAI is emphasized by the widespread adoption of GenAI in technical areas, such as international finance and computer science; both of which are now subject to increasing amounts of automated output that mimic professional competence. These two areas are among the first 'early adopter' fields in the higher education system in East Malaysia to incorporate AI, however, the incorporation of AI into curricula has occurred faster than the creation of a framework at an institutional level for regulating one's own digital behavior [3]. If there is no immediate empirical knowledge of how students in East Malaysia experience their digital literacy vs. digital dependency while navigating the boundaries between them, it is possible that universities will produce students with technical qualifications, but without sufficient cognitive ability to independently solve problems. Therefore, studying the impact of GenAI within these areas with high stakes (i.e., those related to professional certification) is necessary for maintaining regional professional standards.

While policy-based approaches and technical solutions have dominated recent academic discourse regarding GenAI, the internal psychological factors of students who utilize or misuse these technologies have been largely absent from the literature. Personality has long been demonstrated to be a key driver of learning motivation and behavior [8], [9]. As such, this study addresses the identified gap by focusing on internal psychological motivations as opposed to previously discussed external institutional regulations [3]. This study is designed to answer the following scientific question: how do specific personality traits found in the Big five framework—conscientiousness, neuroticism, and openness—predict a student's transition from using AI as an aid to over-relying on it for the completion of academic tasks, and how does this GenAI over-reliance relate to academic procrastination and ultimately impact academic performance? [5]. The present study develops a conceptual model rooted in established personality theory [10] and digital learning contexts [11] to illustrate the relationships between these constructs. Within this framework, 'GenAI over-reliance' is defined as the substitution of GenAI for the intellectual effort required to master course materials. Using quantitative methodology and partial least squares structural equation modeling (PLS-SEM), this research examines academic procrastination as a key mediator between personality-driven GenAI over-reliance and students' academic achievement. Overall, this study aims to provide educators with empirical evidence to move beyond general prohibitions and develop targeted, psychology-informed educational strategies to reduce GenAI-related procrastination.

2. PERSONALITY TRAITS AS PREDICTORS OF TECHNOLOGY ENGAGEMENT

Although psychology provides many theories on how individuals decide to utilise technology, the five core personality traits identified through the Big five theory of personality are the most commonly researched [12]. The reason behind this research focus is based on the fact that many studies confirm that personality traits remain relatively consistent throughout an individual's life. In order to better understand why some individuals quickly accept new technologies, while others resist them, researchers are increasingly including the personality traits (i.e., extraversion, agreeableness, conscientiousness, neuroticism, openness) within the majority of technology usage models (i.e., technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT) [13], [14].

The way individuals engage with digital environments is rarely uniform; rather, it is primarily driven by their core personality traits, which dictate their preferences and behaviours in online spaces. Extraverts, for example, consistently report higher levels of online social network engagement and communication tool utilisation compared to introverts, because extroverted individuals inherently prefer platforms that enable interaction and connectivity [15]. Agreeable individuals exhibit a more nuanced behavioural pattern, as they appear comfortable working collaboratively on common technological platforms, yet are generally hesitant to share their personal information on social media [16]. Conscientiousness tends to serve as a robust barrier against excessive reliance on digital technologies (i.e., smartphone addiction) as the relationship is inverse [17]. Nevertheless, the same need for organisation and planning enables conscientious individuals to readily take advantage of time-saving technologies—for instance, one-click shopping checkout and utilising an e-government portal to renew a license from the comfort of their own home [18]. Conversely, neuroticism appears to be at the opposite end of the spectrum, as anxious individuals are significantly more likely to develop either extremely heavy or compulsive Internet use behaviours, frequently using the Internet as a means to avoid day-to-day stress [19]. On the other hand, highly open-minded individuals tend to treat the Internet as an endless curiosity shop. Therefore, open-minded individuals tend to engage in online courses, view tutorial videos, and consume new information whenever possible [18].

Research supports that the relationship between personality and technology will be a growing concern as students transition from traditional learning environments to an increasing number of technology-based learning environments. Personality will play an important role in determining how well students adjust to new technologies, as well as their motivation and confidence in their ability to learn within these environments [20]. For example, it was found that students who were high in conscientiousness and openness to experience engaged at a higher level in deep learning than those students who did not possess these traits. It also found that students who possessed higher levels of neuroticism had more anxiety-based motivations for using technology compared to other types of motivations [21]. The emergence of GenAI as a primary aspect of technology-based learning environments will create a solid theoretical framework to identify which students are most likely to utilize AI effectively and which students are most likely to over-rely upon GenAI.

2.1. Conceptualization and hypotheses development

In order to determine why some students will accept and others will reject classroom technologies, researchers will need to look at the underlying psychological motivations that drive students' behavior and attitudes toward classroom technologies. A fundamental psychological factor influencing both behaviors and motivations is an enduring dimension of variation among individuals known as personality. One of the better models currently available for charting this territory is the Big five model of personality [10]. The Big five model identifies five dimensions of personality that research has shown to influence numerous aspects of academic success. These include the ability to perform academically [22], the willingness to adopt untested classroom technologies [13], [23], and the propensity for students to either utilize GenAI productively or develop an over-reliance that interferes with their learning [11].

The focus of the present study is on the three personality traits that are most likely to influence how students interact with GenAI: conscientiousness, neuroticism, and openness. For example, the trait of conscientiousness may act as a barrier to the attraction of the quick fix, but, conversely, the lack of conscientiousness may cause a student to be unable to resist the temptation to seek assistance from a chatbot. Neurotic students are often experiencing varying degrees of emotional distress, therefore, they are more likely than other students to seek out quick, anxiety-reducing solutions, such as relying on GenAI for fast relief about course materials. In contrast, individuals who score highly on openness are often curious and experimental learners, and their interest in learning for the sake of learning motivates them to try new tools and approaches to learning. Nevertheless, their ongoing experimentation can lead to a reliance on technology as they integrate it into all of their study processes. This ongoing experimentation may lead to what researchers call a 'competence illusion' [6], where students mistake the machine's efficiency for their own mastery of the course content. Consequently, the next section will outline the theoretical propositions that describe the relationship between each of the three personality traits, and students' propensity of over-reliance on GenAI, as well as the possible consequences on students' procrastination and academic performance.

2.1.1. The allure of a shortcut: conscientiousness

Conscientiousness is one of the two personality traits that have the most consistent and strong associations with academic achievement [22]. Conscientious students exhibit several characteristics that foster a sense of duty, discipline, and a desire to structure their studies [22]. Because of their organizational tendencies, conscientious students create detailed schedules for studying, meet deadlines regularly, and manage procrastination incredibly well [24]. Similarly, when conscientious students choose to utilize GenAI in their studies, they generally use the technology to prompt ideas or assist in refining their drafts, rather than using it to find shortcuts and avoid authentic learning [7]. In contrast, individuals who are low in conscientiousness often lack organization and impulse control, which increases their likelihood of being attracted to the promises of instant answers that GenAI offers [23]. Furthermore, individuals who are low in conscientiousness may rely heavily on GenAI to help them avoid completing challenging coursework. Thus, they may begin to develop a dependency on the technology that undermines their remaining self-discipline [8]. Therefore, based on this logic, we propose that: conscientiousness will be significantly associated with AI over-reliance (H1).

2.1.2. Neuroticism as a driver of dependency

The use of tools for students that produce an immediate answer when confronted with overwhelming academic pressures can be a result of academic anxiety. Large body of research shows that students with higher levels of neuroticism have greater levels of stress and anxiety concerning their academic performance [25]. In situations where students are overwhelmed with workloads, those who are neurotic are likely to utilize GenAI as a way to instantly decrease their anxiety and self-doubts [26]. Although utilizing AI as a means to alleviate anxiety is a short-term solution; relying on GenAI to ease anxiety may pose many long-term implications. More specifically, using GenAI to alleviate their anxiety on a constant basis may limit a student's ability to develop confidence in their academic capabilities [27]. The increased anxiety towards their academic abilities limits the potential to establish confidence in their abilities and will create a vicious cycle where students believe each successive academic task will be more difficult to accomplish; thus, limiting the reliance on GenAI to alleviate their anxiety. Therefore, based upon this dynamic, we propose that: neuroticism will be significantly associated with AI over-reliance (H2).

2.1.3. Openness and technological experimentation

Students who are high in openness exhibit curiosity and a love of learning [27]. These students are also highly motivated to experiment with new tools and technologies [18]. Conversely, students who are low in openness tend to prefer a well-known path and will rarely engage in creative or abstract problem-solving [27]. GenAI represents a powerful technological tool that can serve as a creative partner to students, although the novelty and power of the technology itself attract students who are high in openness [28]. As a result of their curiosity-driven engagement with the technology, students who are high in openness may use the technology frequently. Through repeated experimentation with the technology, they may develop a dependency on it to facilitate their study processes [26]. Therefore, based on this dynamic, we propose that: openness will be significantly associated with AI over-reliance (H3).

2.1.4. AI over-reliance, procrastination, and performance

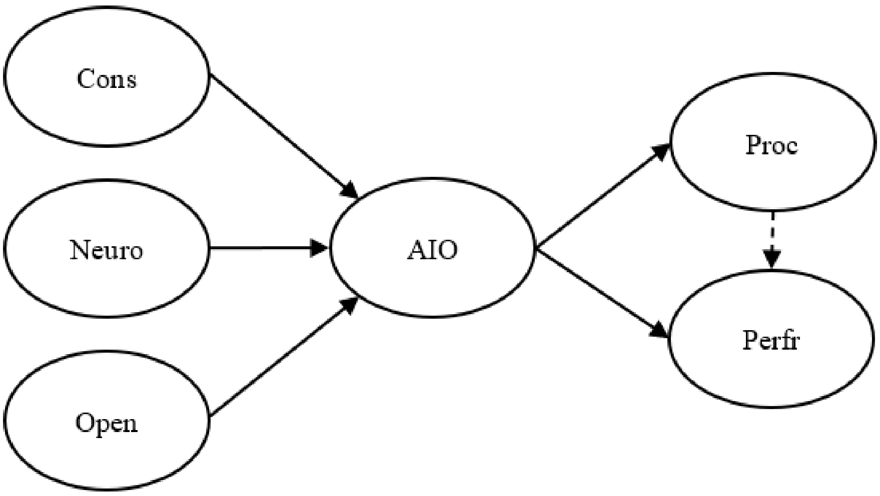
When students use GenAI in a manner that makes it a habitual part of their academic processes, they are engaging in a form of AI over-reliance [3], [29]. In general, this type of AI over-reliance occurs when students regularly depend on the technology to perform academic tasks, rather than investing meaningful amounts of cognitive energy in doing so [29]. Additionally, AI over-reliance does not reflect productive uses of AI as a study tool, such as generating ideas, exploring different perspectives, and refining text previously authored by the student [30]. Instead, AI over-reliance represents a destructive form of procrastination, defined as delaying academic work until the task feels urgent and stressful [24]. This is because AI over-reliance allows students to avoid their academic responsibilities without feeling any immediate consequence, and thus, the technology reinforces the students' procrastination [31]. Finally, because over-reliance on AI promotes procrastination, it also negatively impacts academic performance [3], [29]. As such, we anticipate that: there will be a positive relationship between AI over-reliance and academic procrastination (H4). Similarly, since AI over-reliance hinders students' ability to learn and develop the knowledge, skills, and insights that are required to succeed in assessments and real-world situations, we anticipate that: there will be a negative relationship between AI over-reliance and academic performance (H5).

2.1.5. The mediating role of procrastination

Procrastination is expected to act as a mediator between the variables of AI over-reliance and academic performance since when students rely too heavily on an AI for producing the answers to academic work, they begin to feel reliant upon it; therefore, when students perceive that a chatbot is available to assist with their academic questions at all times, they are likely to develop a sense of security that may reduce their likelihood to regularly commit to studying and increase procrastination [32]. Consequently, procrastination harms academic performance, as last-minute completion of academic tasks often results in hasty work, increased stress levels, and fewer opportunities for revision and reflection [33]. Therefore, based on the theory of temporal motivation, procrastination is proposed to be a mediator of the relationship between AI over-reliance and academic performance because the availability of rewards immediately after completing academic work increases the distance between students' intentions and the actions taken to complete academic tasks, and this distance is widened even further by the immediacy of the rewards offered by GenAI [34]. Therefore, we propose that: procrastination will mediate the relationship between AI over-reliance and academic performance (H6).

3. METHOD

As seen in Figure 1, our research model suggests a causal cascade, assuming that individual disposition leads to an increase in the amount of reliance on technology for completing educational assignments. Specifically, three personality traits (i.e., conscientiousness, neuroticism, and openness) are proposed to be the most influential on a student's likelihood to utilise GenAI for educational purposes. This usage of GenAI is further theorised to increase the likelihood of academic procrastination, as students may put off starting an assignment knowing that they can get instant help from AI, and therefore have less time for the completion of other important aspects of an assignment (e.g., preparation, reflection, and revision). Furthermore, the model theorises a direct negative relationship between excessive use of GenAI and academic performance; however, this relationship is mediated by procrastination.



Note: Cons—conscientiousness; Neuro—neuroticism
Open—openness; AIO—AI over-reliance
Proc—academic procrastination
Perfr—academic performance

Figure 1. Model framework

3.1. Sample and measurement instruments

A total of 200 undergraduate students enrolled in either a Computer Science or an International Finance program participated in this research via purposive sampling. These specific majors were selected as they represent 'early adopters' who frequently integrate GenAI into technical assignments. Data collection occurred solely in the classroom to minimize distractions and was conducted over a four-week period in October 2025. Participation was strictly voluntary and anonymous to promote honest responses.

The measurement tools used for this research were developed using existing and previously validated scales. Personality traits were evaluated using the three big five inventory (BFI) dimensions of conscientiousness (9-items), neuroticism (8-items), and openness to experience (10-items) [10]. The items assessing GenAI over-reliance were adapted from problem-based measures designed to evaluate the development of dependence, as well as habitually relying on GenAI [35]. Academic procrastination was evaluated using items generated from seminal research studies on the intention to delay the completion of academic work [32], [36]. Academic performance was also evaluated through self-report measures where participants were asked to rate how satisfied they were with their current grades [37]. Each item was measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The survey instrument underwent a two-stage validation process before full deployment. First, content validity was established through an expert review panel of three senior academicians specializing in educational psychology. Second, a pilot study with 30 students was conducted to ensure semantic clarity, resulting in minor phrasing adjustments to the personality items to better suit the regional student context.

4. RESULTS

SmartPLS 4 was utilised to apply PLS-SEM to assess the theoretical model via a two-stage procedure: first evaluating the reliability and validity of each latent variable (measurement model) before examining the hypothesized relationships (structural model). PLS-SEM was selected because it is optimized for predictive research and handles non-normal data distributions robustly [38]. Prior to analysis, statistical assumptions were verified; multicollinearity was assessed using variance inflation factor (VIF) values, all of which were below the 5.0 threshold. Finally, bias-corrected and accelerated bootstrapping with 5,000 resamples was used to establish the significance of the path coefficients.

4.1. Model assessment

The measurement model was first assessed as to whether each indicator for each latent variable sufficiently captured the respective theoretical construct it was intended to represent. The results found in Table 1 indicate that all indicators for all latent variables were representative of their respective theoretical constructs. In addition, each of the latent variables demonstrated a high level of internal consistency. Composite reliability (CR) for all of the latent variables were above the 0.70 threshold [38], [39]. Additionally, Cronbach's alpha for all of the latent variables ranged from 0.64 to 0.93 which are within the range of acceptability for exploratory research in the social sciences [39]. Finally, average variance extracted (AVE) scores for all of the latent variables exceeded the 0.50 threshold that has been established as a minimum threshold for the demonstration of convergent validity [38].

Table 1. Model assessment

Construct	Cronbach's α	CR	AVE
Conscientiousness	0.925	0.938	0.628
Neuroticism	0.918	0.933	0.638
Openness	0.937	0.947	0.642
AI over-reliance	0.765	0.851	0.590
Procrastination	0.640	0.811	0.589
Performance	0.652	0.813	0.592

Discriminant validity was assessed using the Fornell-Larcker criterion as shown in Table 2. This criterion requires that the square root of the AVE for each latent variable exceeds its highest correlation with any other latent variable [40]. This ensures that a construct shares more variance with its own indicators than it does with any other construct in the model [38].

Table 2. Discriminant validity

Construct	AIO	CON	NEU	OPE	PERF	PROC
AI over-reliance (AIO)	0.768					
Conscientiousness (CON)	-0.473	0.792				
Neuroticism (NEU)	0.350	0.096	0.799			
Openness (OPE)	0.531	-0.144	-0.019	0.801		
Performance (PERF)	-0.508	0.211	-0.155	-0.410	0.769	
Procrastination (PROC)	0.484	-0.314	0.078	0.376	-0.336	0.767

The structural model's goodness-of-fit was assessed through model fit indices prior to performing path analysis using the data presented in Table 3. A good model fit is demonstrated by the SRMR of .072 which is well below the suggested threshold of <0.08. Further evidence supporting the models' acceptability is provided by the NFI=0.910 which surpasses the benchmark value of >0.90. As well, the model explains a significant portion of the variance associated with the primary endogenous construct, GenAI over-reliance with an R^2=0.601, and provides strong evidence of predictive relevance (Q^2=0.312). These model fit indices collectively demonstrate that the structural model has been established with statistical validity and therefore will serve as a basis for testing the proposed relationships.

Table 3. Model fit

Fit index	Result	Recommended threshold
Standardized root mean squared residual (SRMR)	0.072	<0.08
Normed fit index (NFI)	0.910	>0.90
R^2 (AI over-reliance)	0.601	>0.26
Q^2 (predictive relevance)	0.312	>0

4.2. Hypotheses testing

To enhance the clarity and transparency of the results, descriptive statistics and effect sizes *(f^2)* were calculated for all key constructs. The f^2 values demonstrate the substantive impact of the predictors on the endogenous variables. As shown in Table 4, GenAI over-reliance exhibits a large effect size (f^2=0.43) in relation to academic procrastination, while academic procrastination shows a medium effect size (f^2=0.15) in relation to performance. In contrast, the personality traits of neuroticism and openness show small-to-medium effect sizes, indicating that while they are significant predictors of GenAI over-reliance, the most substantial driver within the structural model is the students' level of dependency on the technology itself.

Table 4. Descriptive statistics and effect sizes

Path	Mean	SD	f^2 (effect size)
Conscientiousness	3.49	0.74	0.02
Neuroticism	3.75	0.74	0.12
Openness	3.59	0.76	0.10
AI over-reliance	3.72	0.66	0.43
Academic procrastination	3.36	0.63	0.15
Academic performance	2.95	0.65	-

Following the evaluation of the measurement model, the next step was to evaluate the structural model. The structural model was evaluated using a bootstrapping procedure with 5,000 resamples [38] to assess the significance of the hypothesized path coefficients. The theoretical model developed in the study explained a substantial amount of the variance in AI over-reliance (R^2=0.601), procrastination (R^2=0.266), and academic performance (R^2=0.295). As presented in Table 5, the results of the path analysis supported all five direct hypotheses (H1–H5) as statistically significant. The results of the path analysis indicated that personality traits of conscientiousness, neuroticism, and openness had a statistically significant predictive relationship with AI over-reliance, which was also positively related to academic procrastination and negatively related to academic performance, as seen in Figure 2.

Table 5. Path analysis

Path	β	t-statistic	p-value
H1 Conscientiousness-->AI over-reliance	-0.444	7.215	0.000***
H2 Neuroticism-->AI over-reliance	0.402	6.840	0.000***
H3 Openness-->AI over-reliance	0.473	7.512	0.000***
H4 AI over-reliance-->procrastination	0.319	4.102	0.000***
H5 AI over-reliance-->performance	-0.368	5.234	0.000***

Note: ***p<0.001

4.3. Mediation analysis

The results of the mediation analysis, conducted using a bootstrapping method, are presented in Table 6. This analysis found that academic procrastination had a statistically significant indirect effect (β=-0.057, p=0.044). The 95% confidence intervals for the indirect effect did not include zero and therefore met the statistical requirements for mediation. Thus, we can conclude that academic procrastination is an intermediate variable; therefore, at least part of the impact of AI over-reliance on academic performance occurs due to increases in procrastination, thereby supporting H6.

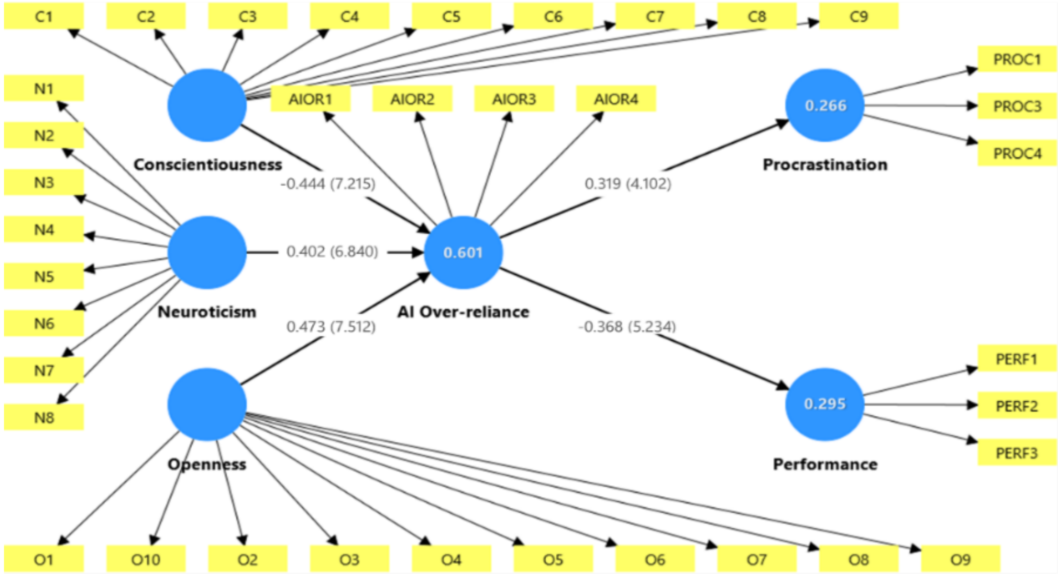


Figure 2. Structural model

Table 6. Mediating test

Path	Indirect β	t-statistic	p-value
AI over-reliance→procrastination→performance	-0.057	1.713	0.044*

Note: *p<0.05 (one-tailed).

5. DISCUSSION

The primary scientific issue being studied by this research is the degree to which internal psychological variables (i.e., personality) influence both the extent to which students rely on GenAI and how AI influences students' academic performance. The study uses empirical evidence, generated through a PLS-SEM analysis of 200 undergraduate students. The use of empirical evidence and the focus on the psychological characteristics of the students is a major departure from most prior studies that have focused mostly on institutional policies.

The findings suggest that personality traits are key determinants of GenAI over-reliance rather than mere correlates. Specifically, the negative relationship between conscientiousness and over-reliance indicates that disciplined students maintain structured routines that prioritize long-term mastery over technological shortcuts [22]. In contrast, those with higher levels of neuroticism tend to utilize GenAI as a 'digital safe space' to mitigate performance-based anxiety [8]. Furthermore, the positive link between openness and GenAI over-reliance suggests that curious students may initially explore these tools for their convenience, which can inadvertently lead to a gradual erosion of academic integrity [18]. Crucially, the significant mediation effect confirms the presence of a ‘competence illusion’ [6]; as students mistake the machine’s fluid output for their own mastery, they trigger a cycle of cognitive deterioration and procrastination. Profoundly, this ‘procrastination trap’ represents a direct psychological consequence of outsourcing intellectual effort to automated systems.

This research offers the educational community a much-needed shift in perspective. We have to stop focusing on how to police technology and start paying attention to the psychological aspect behind its usage. The data clearly indicates that merely restricting GenAI access is not going to be a viable long-term strategy. Instead, institutions need to cultivate genuine AI literacy. Students must be taught to recognize the specific psychological triggers that push them toward dependence. Tackling the ‘competence illusion’ before it can impede and degrade actual learning outcomes is the only way to provide meaningful student support. Building future educational policies around this kind of psychological awareness will be absolutely essential.

6. IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

The first step to solve this problem is to alter the way institutions think about and manage GenAI. Rather than developing new policies based upon a culture of policing and reacting to issues created by technology, we believe universities should be proactive in incorporating GenAI literacy within their core policies [2]. To break the ‘procrastination trap’, and thereby prevent the ‘competence illusion’ that comes with it, educational assessments must undergo a complete transformation. The most effective strategy will be to measure progress during the learning process rather than just after completion. This can be achieved through methods such as written examinations, oral defenses and reflection journals to measure the extent of a student's mental efforts [1]. With regard to policy, we believe integrity codes must clearly differentiate between ‘functional assistance’ and ‘cognitive off-loading’, the latter being an example of where a student becomes so reliant on machines they lose the ability to perform independently [6]. In addition, we propose that each student participate in ‘AI meta-awareness’ workshops designed to identify potential sources of stress related to academic performance, including anxiety and fear, that contribute to students’ reliance on machines [35]. For students whose personality traits make them more likely to struggle, we suggest providing specialized coaching in self-control. This ensures they use GenAI as a tool to assist their work rather than a total replacement for their own thinking [5].

There are several limitations inherent to all studies, and ours are no exception. One limitation relates with the cross-sectional design. The study can only capture one snapshot in time for each student. Therefore, while we know that there exists a relationship between students' personality traits and their level of GenAI reliance, we do not have empirical evidence to support whether personality traits cause students to rely more heavily on machines or whether students' dependency on machines causes them to develop certain personality traits throughout their academic career. The second limitation involves the populations studied. Our research focused on early-adopters in Computer Science and International Finance at a University located in East Malaysia. These populations represent an important initial group; however, their behavior patterns will likely differ significantly from Arts or Humanities students who utilize GenAI to accomplish more subjective assignments. Finally, we relied solely on self-reporting measures of grade point average (GPA) and GenAI usage. Such methodology is inherently flawed because students may either report inflated success rates or minimized levels of machine reliance due to peer pressure or fear of social judgment [37].

In order to build upon the findings of this current study, future researchers should conduct longitudinal analyses of students across their entire four-year undergraduate program. By doing so, researchers will be able to better understand how the ‘competence illusion’ affects skills development both in the short-term and the long-term. To verify if the proposed AI meta-awareness workshops truly make a difference, future researchers should use ‘wait-list’ experiments. This allows for a clear comparison between students who have finished the training and those still waiting to start, proving if the program actually helps. Lastly, large-scale international comparative studies will be needed to determine if the ‘procrastination trap’ represents a global human phenomenon or merely a cultural reaction to rapidly changing digital trends occurring in emerging regional education hubs [7].

7. CONCLUSION

This research shows that there are psychological reasons why students get caught up in the ‘procrastination trap’, and that their reliance on GenAI may have more to do with who they are as people (i.e., personality), than how easy it is to use. The research finds that although GenAI has many functional advantages for students, GenAI can also create a ‘competence illusion’, which can decrease actual academic performance—especially among those students who tend to score high on neuroticism and openness. Ultimately, by defining academic procrastination as the key mediator in the relationship between GenAI and students' academic performance, this research demonstrates that many students’ misuse technology because of a lack of ability to regulate themselves psychologically, not due to a lack of technical proficiency.

The major contribution of this work is that it will cause a paradigmatic shift in the way that academics think about addressing issues related to GenAI; specifically, instead of detecting whether or not a student is using GenAI correctly, we suggest that future research should focus on preventing GenAI misuse through a paradigmatic shift in pedagogical practice. As such, this research serves as the empirical evidence required to advocate for a shift towards process-based assessments and the incorporation of GenAI literacy into university policy. In addition, by providing empirical evidence regarding the role of stable personality characteristics in determining students' likelihood to misuse GenAI, educators are now able to develop better student support systems, including self-regulation programs designed to assist high risk students use GenAI as a cognitive tool or scaffolding for learning, rather than an intellectual substitute. Finally, as GenAI is now so widely used within the higher education sector, it is essential for institutions to be proactive in developing policies that protect the learner’s ability to develop cognitively. As AI will increasingly be ubiquitous in assisting students with their learning, educational institutions must adopt a new pedagogy—science or art of teaching—that values the learning process itself as much as the products generated from those processes.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
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Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
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CONFLICT OF INTEREST STATEMENT

The authors have no financial or personal relationships that could inappropriately influence or bias the content of this study.

DATA AVAILABILITY

The data supporting the findings of this study are accessible through databases indexed by Scopus, Web of Science, and IEEE Xplore. All data utilized in this research are presented within the article through tables, figures, and detailed discussions.

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