



Personality and University Students' Use of Generative Artificial Intelligence: A Review and Pedagogical Framework

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Abstract

Generative artificial intelligence (GenAI) has become a common feature of university life, but the reasons, methods and circumstances under which students use it vary greatly. This paper collects new studies on personality and generative AI use in higher education to propose a Personality-Mechanism-Use-Outcome (PMUO) model. Across the studies reviewed, openness to experience is most consistently associated with favourable evaluations of GenAI, intentions to use it and self-reported educational engagement with it; however, direct evidence on exploratory behaviour and learning quality remains limited. Conscientiousness appears more closely related to planning, monitoring, reflection and sensitivity to task rules than to uniformly higher GenAI use frequency. Associations of Extraversion and Agreeableness vary in different environments. Neuroticism illustrates the need to distinguish among outcomes; it has been linked to lower educational utilisation and a higher perceived cost in some studies, but also to compulsive ChatGPT use. Honesty-Humility, Dark Triad traits, moral identity, degree apathy, perceived risk and moral obligation may offer more proximal explanations for academic risk-taking behaviour than the broad domains of the Big Five, but direct comparative evidence is limited. The proposed PMUO framework treats personality as a distal, probabilistic influence that may operate through modifiable mechanisms, including value, anxiety, self-efficacy, calibrated trust, AI literacy, self-regulated learning, academic engagement and ethical judgment. Most direct research is cross-sectional and self-reported, and some studies focus on general AI rather than GenAI. Causal, diagnostic and individualised instructional claims are therefore premature. Practical applications advocate for universal AI literacy, visible planning and verification routines, transparent assessment rules, independent performance checkpoints, and optional support according to observable learning needs rather than personality labels.

Keywords: Generative artificial intelligence; Personality; Big Five; University students; Self-regulated learning; Academic integrity.

Introduction

Generative Artificial Intelligence (GenAI) has gone from being new to being common in higher education. Students can now use a conversational system to explain concepts, give examples, summarize reading materials, practice language, develop ideas, write or debug code, and receive instant feedback. In a survey of 1,054 full-time undergraduates in the United Kingdom, 95% reported using artificial intelligence in some capacity and 94% reported using GenAI to support assessed work [1]. These figures are specific to the UK survey context and do not show the quality of use; however, they do indicate that GenAI is no longer a marginal educational technology. The educational consequences of this transition are conditional. Generative AI can provide clear explanations, customised examples, formative feedback and language

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support; at the same time, it is also prone to generating inaccurate or misleading information, biases and plausible but unverified content [2]. A recent meta-analysis reported positive average effects of GenAI on intellectual and social-emotional outcomes in higher education, although substantial heterogeneity, sensitivity to individual studies and evidence of publication bias for intellectual outcomes warrant caution [3]. Therefore, the same tool can be used to support learning or to replace the thinking that a task is intended to promote.

Students exposed to the same tools and institutional rules use GenAI in different ways. Some students use GenAI to explore new ideas, compare options and test their understanding. Others perform routine editing or formatting. Others submit the generated work in violation of the course rules, accept the output without checking it, or are unable to proceed independently. Use frequency alone cannot distinguish these patterns. High use may be due to continuous learning, effective help or lack of control; low use may be caused by lack of access, anxiety, low perceived value, institutional restrictions or a desire for independence. Personality offers one framework to explain the reasons for different responses to newness, effort, uncertainty, socialisation and rules. The Big Five are general attributes: Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism [4]. Meta-analytic evidence shows that these traits are associated with information and communication technology use, although the associations vary by technology and context [5]. Traits are regarded as distal, probabilistic tendencies in this review, and their expression is affected by knowledge, motivation, task demands, prior experience, teacher guidance, assessment design, institutional policies, etc. They are not considered fixed types of students or adequate explanations for behaviour.

Evidence linking personality to university students' GenAI use is growing but remains fragmented. The reviewed studies examine acceptance, intention, self-reported educational use, learning motives, self-regulated learning, resource preference, academic misconduct, overreliance and compulsive use, and include contextual evidence on general AI and adult populations [6-13, 15-22]. The results are not interchangeable: favourable attitudes alone do not establish actual behaviour, frequent use alone does not establish constructive engagement, substitutive use is not always prohibited, and compulsive use is different from deliberate academic dishonesty. This review therefore examines how personality relates to different forms of AI engagement and which modifiable mechanisms may connect these relations to learning, integrity and well-being. It proposes a PMUO framework and derives personality-informed, needs-responsive teaching ideas without labelling or profiling students.

Conceptual Foundations and Scope of the Review

Personality, Related Dispositions, and Modes of GenAI Use

Generative AI is a system that can generate new text, code, images, audio and other kinds of content based on natural-language or multi-modal prompts, as shown in this review. The personality studies reviewed here predominantly concern large language model-based conversational systems, such as ChatGPT; therefore, the results should not be automatically applied to image generators, code assistants, multimodal tutors, or future embedded systems [2, 23]. The Big Five provides a convenient common vocabulary. Openness refers to curiosity, imagination and a desire for new experiences; Conscientiousness is about organisation, diligence and goal-orientation; Extraversion is related to sociability and activity; Agreeableness involves cooperation, empathy and trust; Neuroticism is linked to anxiety and negative emotions [4]. These are continuous characteristics and not fixed categories of students. Broad personality domains may conceal relevant facet-level associations, and adequately validated measures are preferable when small, context-sensitive effects are expected. The Big Five alone may be insufficient to explain ethically consequential or poorly controlled behaviour. The six-factor HEXACO model includes Honesty-Humility, which encompasses sincerity, fairness, modesty and a lack of an interest in the exploitation of others [49]. The Dark Triad refers to the distinguishable but overlapping traits of Machiavellianism, narcissism and psychopathy [50]. Other relevant variables, which should not all be treated as personality traits, include moral identity, degree apathy, perceived risk, AI self-efficacy and AI literacy. Some of these variables are more domain-specific and may offer targets for educational support, although intervention effects require direct testing [17-22].

For analysis, this paper classifies the use of GenAI by function, authorisation and retained human cognitive involvement. Exploratory Use is the test of a new or potentially useful system. Constructive and self-regulated use uses GenAI for explanation, feedback, planning, comparison, verification and reflection, and retains human judgment. Instrumental Use refers to the division of ordinary tasks such as editing, translation, formatting or generating the first examples, and is neither inherently good nor bad. Substitutive use delegates or replaces the main intellectual activity that a task is to promote, regardless of whether the use is permitted. Academically unauthorised use is in direct violation of the explicit rules or disclosure requirements, and it is not the same as substitutive use. Dependency-related use refers to decreased independent control or an inability to complete

appropriate academic work without AI. Compulsive use is a particular type of self-reported behaviour and should not be considered a clinical diagnosis [15, 22]. The same student may use these modes for different purposes and at different times.

Acceptance, intention, behaviour, use quality and outcomes must also be separated. Within the Technology Acceptance Model, perceived usefulness and perceived ease of use are distinct constructs [24], and the Unified Theory of Acceptance and Use of Technology incorporates social influence and facilitating conditions [25]. Here, acceptance is an evaluation; intention is a stated likelihood of use; self-reported use is a retrospective account; observable behaviour requires task records or interaction traces; use quality needs verification and appropriate human control; and educational outcomes require evidence such as achievement, retention, critical thinking, integrity or well-being.

The proposed Personality–Mechanism–Use–Outcome framework

The PMUO framework hypothesises that personality acts as a distal influence whose consequences may depend on proximal processes. At the first level are the Big Five and related dispositions, including Honesty-Humility and socially aversive traits. Second are perceived value and cost, AI anxiety, self-efficacy, calibrated trust, AI literacy, self-regulated learning, moral identity, academic engagement and perceived risk. The third type is exploratory, constructive, instrumental, substitutive, academically unauthorised and dependency-related modes of use. The fourth are learning, engagement, critical thinking, academic integrity and well-being. Discipline, educational stage, type of task, culture, previous experience, assessment design, teacher guidance and institutional policies may moderate the connections among these levels.

The framework is based on the expectancy-value theory of GenAI perception [26], cyclical models of self-regulated learning [27,28], and multidimensional concepts of AI literacy [29]. It is a hypothesis-generating system and not an experimentally verified causal model. Its purpose is to distinguish evidence-supported associations from mechanisms that require direct testing and to guide educational action towards variables that can be changed. The evidence included here mainly consists of peer-reviewed studies of university students available by July 2026, as well as basic theory, meta-analyses and authoritative guidelines. Where GenAI-specific evidence is lacking, studies of general AI attitudes or applications are used as indirect contextual support. Cross-sectional path and mediation models are interpreted as associations rather than demonstrations of time- or cause-and-effect processes.

Personality, Adoption and Learning-Oriented Use

Openness and Conscientiousness

Across the studies reviewed, openness to experience shows a recurrent positive association with favourable GenAI evaluations and self-reported educational engagement with GenAI. Among the 1,016 Turkish students who had already used GenAI educationally, openness was positively correlated with self-reported educational use, and in a neural network analysis, it was the most influential personality predictor [7]. It was also linked to higher acceptance among the 476 pre-service teachers [8]. In a study of general AI use motives, Yurt [9] found that openness was positively associated with attainment, utility and intrinsic value, and negatively associated with perceived cost. Jiang and colleagues [10] identified three distinct canonical functions relating sets of personality traits to sets of GenAI perceptions in a university-student sample. In the first function, higher Openness, Agreeableness and Conscientiousness were positively associated with more AI knowledge, and to a small extent, with a higher perceived cost. In the second, higher neuroticism was associated with a higher cost and lower utility and attainment value. In the third function, lower neuroticism together with higher openness and conscientiousness was associated with greater attainment value, stronger intention to use GenAI and lower perceived cost [10].

These findings are consistent with the possibility that curiosity and tolerance of novelty facilitate favourable appraisal and experimentation, but they do not demonstrate that open students verify outputs or learn more effectively. Boundary Findings Matter. Among foreign-language learners, a measure of intellect/imagination was negatively correlated with attitude, frequency and perceived usefulness [11]. In a United States sample, the same general category was associated with a preference for traditional resources over GenAI [12]. The reasons for these differences may be instruments, task domains, prior experience and sampling. Therefore, openness is better regarded as a potential promoter of favourable appraisal and willingness to participate rather than an index of high-quality use.

Conscientiousness appears more closely related to organisation and regulation than to use frequency alone. It had the largest positive coefficient in the linear model of educational use reported by Arpaci and others [7]. In Weng and colleagues' multivariable path model, conscientiousness was positively associated with forethought and self-reflection in self-reported ChatGPT-assisted learning, but its association with the performance stage was not statistically significant [6]. It was also linked to acceptance by pre-service teachers [8] and contributed to value- or motivation-patterns in [9] and [10]. Conversely, conscientious students in one United States

study reported less use of GenAI after demographic control [12], while conscientiousness was positively associated with attitudes towards AI and use frequency among foreign-language learners [11]. Conscientiousness has also been negatively associated with cheating intention and self-reported misconduct [17, 18]. Together, the above results are in line with, but do not directly show, the interpretation that conscientiousness is related to more deliberate, organised and standardised behaviour. These findings suggest that conscientious students' engagement with GenAI may be sensitive to task value, accuracy requirements and explicit rules.

Extraversion, Agreeableness and Neuroticism

Extraversion and agreeableness show less stable patterns of association. Extraversion was positively correlated with educational use [7], all three self-reported stages of GenAI-supported self-regulated learning [6], favourable attitudes [18], and a preference for GenAI over traditional resources [12]. The above results may indicate active participation in the interactive environment, but conversational preference has not been directly observed. Agreeableness was not an independent predictor of educational use in one study [7], but it was associated with self-reported forethought, performance and reflection [6], and with greater GenAI acceptance among pre-service teachers [8]. In contrast, more agreeable students in another sample perceived less positive academic impact and showed stronger ethical concern [12]. Agreeableness was also negatively associated with both misconduct and compulsive use [15, 18]. In a large-scale study of the attitude towards general AI among adults, only agreeableness of the Big Five traits was independently linked to a more positive attitude; openness narrowly missed conventional statistical significance [16]. Cooperation, norm sensitivity, caution and generalised trust may be in conflict; therefore, a single trait-use rule is not practical.

Neuroticism illustrates the need for outcome-specific interpretation. It showed a negative correlation with educational use among the existing users [7], and multivariate analysis found that higher neuroticism was associated with a greater perceived cost and lower utility or attainment value [9, 10]. Emotional stability generally refers to the low-neuroticism pole, and it has been linked to more positive perceived learning effects and less worry [12]. Yet neuroticism was positively related to use frequency among foreign-language learners despite less favorable attitudes [11], and it was positively associated with compulsive ChatGPT use among Chinese students [15]. Sensitivity to uncertainty may prevent adoption in one environment but promote repeated consultation in another. Reassurance-seeking is a possible reason, but it has not been directly observed in these studies; neuroticism is a trait rather than a clinical diagnosis.

Recent medical-education studies of general AI have further shown task and measurement dependence. Among the 253 Chinese medical students, Openness and agreeableness were associated with both higher positive-attitude scores and higher negative-attitude scores (reverse-coded, with higher scores indicating greater tolerance of AI limitations); Conscientiousness was related to lower positive-attitude scores; Neuroticism was associated with lower negative-attitude scores [51]. Among the 661 senior pre-clinical students, neuroticism was associated with a lower overall frequency of AI use and greater privacy concerns; openness and conscientiousness were linked to selected task-specific applications; and openness, conscientiousness, and agreeableness were associated with more positive perceptions of educational and clinical benefits [52]. As these studies focused on general AI and used various personality scales, including a very short one in [52], they should be regarded as contextual evidence rather than direct replications of the results of generative AI.

Sampling and Context help explain the apparent contradictions. Arpaci and others excluded the 784 non-users and modelled variation among existing GenAI users [7]; studies involving users and non-users focused on adoption or resource preference [12, 13]. Institutional permission, task utility, discipline, language background and previous experience can alter dispositional tendencies. In a survey of 1,001 United States students, reported use differed by student characteristics, major, institution type, task, and policy; institutions permitting ChatGPT had higher reported use [13]. Personality is associated with some of the variation among students; access, norms and task conditions are also factors. Evidence from large adult samples also suggests that domain-specific appraisals may be more strongly associated with use frequency than broad personality traits; in two large-scale surveys, perceived effectiveness and concerns were more closely linked to frequency, and Machiavellianism showed modest associations with use frequency and opportunistic attitudes towards undisclosed use; only about one-fifth of the respondents were students [14].

Proximal Learning Mechanisms

Self-regulated learning offers a reasonable conceptual path for personality and learning quality. Zimmerman's cyclical model of self-regulated learning distinguishes forethought, performance and self-reflection [27, 28]. Students determine the problem and set goals and strategies before using GenAI. During performance, students monitor comprehension and adjust their approach. During self-reflection, they evaluate outcomes and revise future strategies. Although GenAI can support each phase, it may also replace the establishment of goals, lead to a superficial sense of achievement in fluent answers, and thus obscure what a learner can achieve

independently. In a cross-sectional study of 409 university students, a multivariable path model showed positive associations of openness, extraversion and agreeableness with all three self-reported phases; conscientiousness was positively associated with forethought and self-reflection, whereas its path to performance and all three paths from neuroticism were not statistically significant [6]. These results identify variation in perceived regulation; they do not demonstrate observed verification behaviour, causal effects or objective learning gains. Motivation may be used to guide behaviour. Research on expectancy value shows that perceived value and cost are related to the intention to use GenAI [26], and studies of personality motives link openness and conscientiousness to several value configurations and neuroticism to higher costs [9, 10]. Relevance, Direction, Workload and Rules can change values and costs; therefore, they are more actionable than attributes.

AI Literacy and Calibrated Trust can help determine whether experimentation is learning. AI literacy includes understanding, purpose-driven application, critical evaluation, creation and ethical awareness [29]. It also has source verification, uncertainty recognition, privacy protection, and determination of when a human review is needed, etc. In a survey of 257 students at a university in China, AI literacy and self-regulated learning were positively associated with self-reported writing performance, and AI literacy was also associated with GenAI digital well-being [30]. The studies reviewed here do not establish AI literacy as a mediator of associations between personality and GenAI-related outcomes. Trust is also relative. In broader research on AI acceptance, rather than GenAI-specific educational use, openness was associated with AI acceptance among 716 university students, and the model indicated a significant statistical indirect association through AI trust, but not through AI anxiety alone [31]. The study also reported a small sequential indirect association through trust and anxiety, but its cross-sectional design does not establish temporal ordering or causal mediation. In language learning, a mixed-methods study involving a survey of 682 students and 40 interviews found statistical indirect associations between trust and intention through reliance and resistance; self-directed learning moderated the intention-use association, and qualitative findings identified perceived risk as a potential boundary condition [32]. Therefore, the learning goal of this paper is to achieve calibrated trust rather than maximal trust; that is, students need to learn when to be confident, when to seek external verification, and when to apply independent or expert judgment.

Average performance gains should not be mistaken for lasting learning. A systematic review of 69 experimental studies reported positive average effects of ChatGPT interventions on academic performance, affective-motivational states, and

higher-order-thinking propensities, together with reduced mental effort [33]. However, in a controlled inquiry task, ChatGPT users reported lower cognitive load but produced weaker reasoning and argumentation than students using the traditional search method [34]. Cognitive ease may free up resources for synthesis but can also hide substitution. Therefore, independent initial attempts, source verification, explanation of revisions, and delayed transfer tasks are defensible design proposals; however, their actual effects need to be verified in various tasks and student groups.

Personality and Academically Risky or Dependency-Related Use

Academic Misconduct and Irresponsible Use

Risk should be defined in relation to learning objectives, authorisation and disclosure. Permitted brainstorming, language revision or explanation does not constitute the submission of undisclosed generated work in lieu of assessed reasoning. Substitutive use may be permitted in a task that specifically evaluates editing or criticism; however, use may still be academically unauthorised if it violates explicit rules or disclosure requirements, even when the student has completed most of the intellectual work independently. Pedagogically unproductive use may be disclosed and technically permissible; prohibited substitution may be deliberate without being compulsive; and fabricated evidence or references present a different risk again [23, 36]. Among the studies reviewed, one of the most obvious direct personality traits of misconduct is dishonesty. Greitemeyer and Kastenmüller found that Honesty-Humility, conscientiousness and openness were negatively correlated with the willingness to use chatbot-generated text for academic cheating, while Machiavellianism, narcissism and psychopathy were positively correlated; the fairness facet of Honesty-Humility was particularly informative [17]. In a preregistered study of 864 Chinese students, the reported regression analyses linked higher Honesty-Humility, agreeableness and conscientiousness to less self-reported GenAI misconduct, and higher narcissism and psychopathy to more misconduct [18]. Machiavellianism was included in the final misconduct model, but its coefficient was not statistically significant. The discrepancy may reflect differences in the assessed outcomes (hypothetical willingness versus self-reported frequency), instruments, cultures and definitions. Neither study identifies which individual students are more likely to engage in cheating according to personality scores.

Proximal academic and moral variables may be more actionable. Among 160 psychology undergraduates, higher degree apathy was associated with greater willingness to use ChatGPT for assignment writing, whereas conscientiousness, agreeableness, Machiavellianism, narcissism, prior academic performance and study-skills self-efficacy were not significant

predictors of willingness; willingness was also higher under lower detection risk and milder punishment [19]. Moral-identity internalisation was associated with a lower reported use of ChatGPT for ready-made written work in an early 2023 student sample [20], although unreliable Big Five scores were appropriately excluded from the analysis. Perceived risk was negatively correlated with the frequency of use and future intention, and statistically mediated the relationship between perceived academic dishonesty and usage behaviour [21]. In a preregistered study of 2,883 students from 15 countries, more favourable attitudes towards AI academic misconduct, higher perceived AI proficiency, weaker moral obligation and past misconduct were associated with a greater probability of reporting any misconduct intention and greater intensity among those reporting an intention. Weaker subjective norms against misconduct predicted whether any intention was reported, but not its intensity [35]. Therefore, the emphasis has moved from fixed attributes to participation, moral awareness, norm and opportunity structures.

Elhami Athar's Academic AI Usage Inventory Academic AI Usage Inventory categorizes constructive, overreliant, and irresponsible use [22]. In a sample of 171 university students, disinhibition and antagonism were associated with irresponsible use, disinhibition with overreliance, and anankastia with more constructive and less irresponsible use. The divisions are convenient, but the tool was developed in a relatively small, heterogeneous-age group and needs to be replicated, measured-invariance tested and behaviourally validated. It should not be used for disciplinary screening.

Over-reliance and Compulsive Use

Overreliance concerns diminished independent control rather than high frequency alone. Hu and others found that, after controlling for age, neuroticism was positively associated with compulsive ChatGPT use; agreeableness was negatively associated, but openness, conscientiousness and extraversion were not significantly related [15]. Emotion regulation, reduced confidence in independent decision-making and reassurance-seeking are possible explanations rather than mechanisms established by the evidence reviewed here. The study does not establish clinical addiction. These associations motivate at least two provisional explanatory routes. An academically risky or deliberately substitutive route is suggested by associations of lower Honesty-Humility, socially aversive traits, higher degree apathy, favourable misconduct attitudes, weak moral obligation and weaker norms against misconduct with assignment-writing intentions, misconduct intentions or self-reported misconduct [17-19, 35]. Lower moral-identity internalisation and lower perceived risk have also been associated with self-reported assignment use and general ChatGPT use, respectively, but these findings do not establish unauthorised use [20, 21].

A dependency-related route has directly linked evidence of neuroticism and disinhibition with compulsive or over-reliant use [15, 22]. Low confidence, poor self-regulation and repetitive reassurance-seeking are still plausible but under-researched reasons. These routes can overlap and can change across assignments.

Workload and time pressure have also been associated with greater reported ChatGPT use, without establishing whether the use was constructive or risky [37]. Deadlines, grades, policy clarity, access to human support and perceived task value may shape how dispositional tendencies relate to use. Therefore, the educational response should focus on mechanisms and observable deficiencies, such as an inability to initiate, verify, transfer or complete appropriate work without AI, rather than identities or raw frequencies.

Pedagogical Implications

Universal Foundations and Optional Supports

A personality-informed, needs-responsive way of supporting all students should be employed, and instructions, limitations or punishments should not be based on personality scores. Current evidence is correlational, context dependent, and insufficient to establish stable learner types or effective personality matching. The following strategies are Design Implications to be tested, not validated trait-specific prescriptions. A defensible model should combine a universal foundation with optional scaffolds and student choice. When personality is employed in research, participation must be voluntary, informed, low-risk and subject to data minimisation. Scores should not be used to predict misconduct, determine access to GenAI, or affect grades [23, 45].

The general foundation is AI literacy. Students should understand the capabilities and limitations of AI tools, check claims against authoritative sources, identify unverifiable references, protect confidential data, recognise bias, and disclose consequential AI assistance. Guided practice, rather than a single tool demonstration, is used to foster literacy. A process-oriented 16-week study found that students' GenAI literacy evolved through repeated experimentation, metacognitive reflection, ethical deliberation and the construction of personal workflows [38]. One practical task design is to require an initial judgment, the prompt and output, comparison with primary sources, an error log, a revised response, and a statement of the human contribution. Thus, the evaluation and revision will be visible and not a hidden occurrence of tool use.

Planning, Verification and Calibrated Trust

Process scaffolds can reduce reliance on spontaneous self-organization. Before using GenAI, the student can set a goal for the task, record the first answer or hypothesis,

specify the required help, and set evaluation criteria for the output. A short log of the usage will record the following: prompts, checked sources, rejected suggestions, revisions, and a stopping condition. Then the students can explain what has changed and what they can do by themselves now. These factors externalise forethought, monitoring and reflection, and can be gradually reduced with increased competence [6, 27, 28]. Open-ended experimentation should generally be paired with verification requirements to reduce uncritical acceptance. A cycle of "generation, comparison, verification and justification" can be employed to explore newness responsibly. Hesitant students can be given worked examples, low-stakes practice, predictable rules, and an equivalent AI-free path unless AI literacy is also to be learned. Confidence-calibration activities can have students predict the answer before consulting the AI, rate their confidence in the AI's response, check external evidence, and explain any changes. Stop rules can specify when further prompting no longer improves understanding and when human help is preferable. The above strategies can address observable curiosity, anxiety and the need for reassurance without labelling students as open-minded or neurotic.

Independently preserve the capacity for self-management. Examples include an AI-free initial attempt, waiting to access it until a plan was generated, retrieval practice before consultation, comparison of personal and AI-generated solutions, and independent completion of transfer tasks. Good non-AI assessments may be suitable if the learning objectives are clearly independent recall, reasoning, communication or professional ability; they should not be symbolic punishments. Concern should focus on whether students can initiate tasks, verify outputs, transfer learning, and complete appropriate work without AI, rather than on raw use frequency [15, 22, 34]. Direct experimental work is required to determine which of these designs improve learning, for whom, and under what circumstances.

Integrity and Assessment Design

Academic integrity education should combine clear assignment-level boundaries, worked examples, disclosure practice, and moral reasoning. General statements that AI is "allowed" or "forbidden" are insufficient, as brainstorming, translation, editing, code generation, source discovery and the creation of assessment materials all involve different degrees of intellectual delegation. Explain the purpose of protection for each restriction and provide examples of allowed, conditional, and prohibited use. Students can learn to create an AI-use statement by recording the system, purpose, scope, verification steps and responsible parties.

Evaluation is a relatively powerful institutional tool for aligning Generative AI with education. Rather than constructing an "AI-immune" system, one can create a

reasoning and revision process by means of staged proposals, annotated transcripts, source-verification appendices, oral defenses, personalised or local cases, in-class checkpoints, and reflective explanations of rejected suggestions. Rubrics can differentiate between final-product quality and the use/reasoning/revision of evidence. Chan's policy system includes training, attribution, privacy, accountability, balanced adoption and student participation [39]. The Artificial Intelligence Assessment Scale links allowed AI use with desired learning outcomes [40], and a scoping review has proposed assessment designs that promote self-regulation, responsibility and integrity [41]. No single Design can solve the problem of misconduct, and process documentation can create accessibility and workload burdens; requirements should be proportionate and adaptable.

Educational Stage and Professional Responsibility

Undergraduate education should focus on basic literacy, "think first, ask later", source verification, and regular disclosure. Scaffolds will be gradually withdrawn as students gain independence in evaluation and transfer. Postgraduate and research education need to focus more on authorship, methodological transparency, reproducibility, confidential data, and the division between language assistance and intellectual contribution. Supervisors and students should agree in advance on how GenAI will be used for literature discovery, coding, analysis, drafting and editing, and generated citations, code and analytical decisions must be independently verified. According to the editorial guidelines, AI tools do not qualify as authors, and the human author is responsible for the published work [42]. Accuracy, confidentiality and the risk of harm to individuals are prioritized over convenience in professional programs. Health-professionals' students should verify the results with clinical evidence, recognise unsafe advice, and not enter patient information into unauthorised systems. Ethical guidance for health-professions education includes privacy, consent, ownership, security, bias, transparency, accountability, autonomy and beneficence [43]. Pre-service teachers need to be aware of potential biases, children's data, age-appropriate applications, and professional role models. Case-based simulations can have students identify an AI error, explain the possible consequences, and put forward a reasonable correction. Across stages and disciplines, teaching should respond to mechanisms and demonstrated learning needs rather than presumed personality identities.

Limitations and Future Research

Study identification in this narrative review may be incomplete in a rapidly developing field; no formal risk-of-bias instrument was used, and heterogeneity in populations, measures, tasks and outcomes prevented quantitative synthesis. Some cited studies only report general attitudes

towards or uses of AI, and do not present specific educational behaviour by generative AI. The proposed PMUO framework is conceptual and has not been tested as a complete causal model. The foundation of evidence also has some deficiencies.

First, "GenAI use" is operationalised as attitudes, acceptance, intention, frequency, educational use, self-regulation, misconduct, overreliance or compulsion. Do not combine these constructs into a single index. In the future, the tool and version, task, permitted assistance, disclosure rules, human contribution, and whether the outcome is self-reported, trace-based or independently assessed should also be recorded.

Second, most research uses the same cross-sectional questionnaire to collect data on both personality and AI. The above designs are vulnerable to recall bias, social desirability bias and common-method bias [46], and cross-sectional indirect effects cannot establish longitudinal mediation [47]. The Design should be able to separate the measurement of traits, mechanisms, behaviours and outcomes over time; combine validated scales with interaction traces, verification behaviour, independently scored work and delayed AI-free transfer; and pre-register competing causal models.

Third, Measurement and Sampling Differ Significantly. Ultra-short personality inventories may have low reliability and poor facet coverage; the BFI-2 provides broader domain and facet measurement when assessment burden permits [44]. For example, the task-specific results of [52] should be considered in light of its use of the Ten-Item Personality Inventory. Studies limited to existing users cannot explain non-adoption. Future research should distinguish never-users, former users, occasional users and regular users, and model adoption separately from intensity, authorisation, quality and dependency-related impairment.

Fourth, the current samples are concentrated in a small number of countries, disciplines and undergraduate populations. Coordinated multinational research should carry out measurement invariance tests before comparing pathways [48], and directly measure language, access, socioeconomic resources, prior experience and policy exposure, rather than using country as a crude indicator for culture. Personality data and interaction logs are private and should not be used to grade, predict cheating behaviour or take disciplinary action [45]. Finally, the reviewed evidence does not demonstrate that matching instruction to personality improves learning, integrity or well-being. Longitudinal and experimental studies are needed to determine whether universal and optional scaffolds enhance the observed verification, independent transfer and responsible use; investigate whether their effects differ under different trait configurations; and ascertain whether there are any educationally significant differential effects. Such studies should monitor fairness, privacy, stigma,

accessibility, workload and unintended consequences. With the accumulation of evidence, a pre-registered systematic review and meta-analysis can be conducted on sufficiently comparable outcomes.

Conclusion

Personality is related to university students' engagement in GenAI, but the specific form of this engagement varies. Openness is most consistently associated with positive evaluations, intentions and self-reported educational engagement with GenAI in the studies reviewed; however, direct evidence of exploratory behaviour and learning quality remains limited. Conscientiousness appears more closely related to planning, organisation, adherence to rules and monitoring behaviour than to uniformly higher GenAI use frequency. Associations of Extraversion and Agreeableness remain context dependent. Neuroticism may be linked to lower educational use of GenAI, higher perceived costs, and compulsive consulting. Honesty-Humility and socially aversive traits are linked to risky behaviour; however, degree apathy, moral identity, perceived risk, moral obligation, norms and workload may provide more immediate reasons for certain choices. The PMUO framework hypothesises that modifiable motivational, emotional, self-regulatory, epistemic and ethical processes connect personality to modes of use and outcomes. Its practical implication is not personality classification. Higher education should build universal AI literacy, transparent task-specific rules, process-visible assessment, planning and verification routines, calibrated trust, independent-performance checkpoints, and accessible human support. Optional scaffolds can respond to hesitant exploration, weak planning, uncritical acceptance, or difficulty working without AI while remaining available to all students. The main goal is responsible intellectual agency: the educational value of GenAI lies not only in what the technology can produce but also in how students learn to question, regulate, verify and ethically integrate the output of GenAI into their own work.

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