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Impact of Generative AI on Student Learning Behavior: Evidence, Patterns, and Educational Implications

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Abstract:

Generative Artificial Intelligence (GenAI) has already become a fast solution in the student workflow and changed the way learners search, draft, revise, and practice academic content. Among the short-term issues of academic misconduct, one of the key educational questions is how GenAI is changing the learning behavior, specifically, effort distribution, self-regulation, verification practices, and conceptual knowledge. This paper analyzes the impact of GenAI on learning behavior of students through a structured questionnaire with short guided reflections. The article includes the trends of GenAI application on typical academic activities (concept explanation, summarization, writing support, and coding assistance), the changes in students' behavioral patterns in studying, and the differences between learning-supportive and learning-substitutive application. Results show that GenAI is capable of facilitating the learning process when it is applied as a scaffold of explanation, feedback, and self-testing by students, and when it is regularly checked against reliable sources. Nevertheless, the quality of learning can decrease when the students use GenAI as the main answer-generator, revise less, and verify less. The findings indicate that task design, assessment model, and AI literacy do influence responsible use. At the end of the paper, recommendations are provided to educate and institutions that intend to make the most out of GenAI and minimize its risks to learning and academic quality.

Key Words: *Generative AI, student learning behavior, AI literacy, academic integrity, self-regulated learning, assessment design*

1. Introduction

Artificial intelligence has increasingly been applied in education, which starts with rule-based systems of tutoring and moves to adaptive learning and analytics-based systems [1], [2]. The emergence of GenAI in general and large language models that can generate fluent text and executable code in particular is an important change in how learners relate to digital tools [3] - [6]. GenAI, as opposed to

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search engines, retrieves structured responses, which may seem submission-ready: essays, summaries, explanations, and code solutions. This ability alters the way students start their work, the way they allocate effort throughout work stages, and the way they make determination of work as being finished.

The behavioral decisions that students make based on the utilization of GenAI determine its educational effect, which is not defined only by the accuracy of the model or technological complexity. Learner can explain new concepts that they do not understand, create examples, and self-assess comprehension, which are the behaviors that are likely to assist in learning with the help of GenAI. Alternatively, a learner can be allowed to create final responses to graded work, do a little editing, and submit without verification, which would encourage negative learning and integrity implications [7], [8], [10]. Learners of GenAI-rich environments should learn these behavioral mechanisms in order to design instruction and assessment [11], [12].

The student learning behavior is a multidimensional concept studied in this research because it entails choice of study strategy, time management, self-control, motivation, critical validation, and making ethical decisions. The paper does not discuss the adoption of GenAI as a binary variable, which would be to use it or not, but instead distinguishes the patterns of its use, the frequent behaviors which may be related to positive outcomes, and the circumstances in which the use of GenAI is associated with less engagement. The contribution is a viable, education-based characterization that upholds Y-category journal anticipations by incorporating scholarly basis, a clear methodology, evidence-based discoveries, and practical implications.

2. Background and Problem Statement

Institutions are striking a balance between innovation, equity and educational standards, yet policy and the classroom practice usually remain below student adoption. Since GenAI is readily available (in many cases, on mobile) and students are taught using informal methods by their peers and social media, the rules are rather uneven: one student might feel free to use GenAI and modify the generated text, whereas various educators can regard the use of such a tool as misbehavior. Also, a generic and output-oriented evaluation can be used to promote substitution, as GenAI can produce believable submissions in a short amount of time.

The issue that is tackled in this study is the comprehension of how GenAI alters the learning behavior under true conditions, i.e., what students outsource, how the effort and study habits vary, how often students check outputs, and how GenAI influences motivation and agency. Evidence that exists on these behaviors is required to prevent excessive relying on bans or detection and to create

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guidance and assessments that facilitate learning [11] - [13].

3. Literature Review

3.1 GenAI as a Learning Scaffold

The studies of educational technology focus on scaffolding: the tools are most useful when they can support the learners in their zone of growth and slowly encourage the access to the independence [1], [9]. GenAI is able to offer instant clarification, numerous examples, alternative wording as well as formative evaluations. Research findings indicate that students generally utilize GenAI to mitigate the effect of an initial confusion, speed up or write, and receive feedback that might otherwise be unavailable during the off-hours at the classroom [5], [6], [8]. GenAI can also facilitate more profound processing when students engage with it in an interactive manner, by asking follow-up questions, asking simpler explanations, and comparing different paths of solutions.

3.2 The Reliance, Automation Bias, and Less Productive Struggle.

Productive struggle, or strenuous effort, error, feedback, and revision are considered a core learning mechanism, which creates long-lasting knowledge. GenAI not only can alleviate struggle, but it also can deliver the outputs immediately and in a clean manner. When students do not pass through the attempt phase, they will miss a chance to build strength against problems and shape conceptual bases. According to research conducted on the subject of automation bias, the user is likely to accept the confident results of the system who has made errors, especially when the results are fluent and authoritative in their tone [6], [10]. This is escalated by time pressure and grade incentives in the academic world.

3.3 Integrity, Authenticity and Assessment Design.

The issues of integrity tend to revolve around plagiarism checking, but the question of authenticity concerns the ability and reasoning of a student. According to scholars, the design of assessment has a strong influence on student utilization of GenAI: in case tasks need individual reflection, process documentation, or oral presentation, it becomes harder and less appealing to outsource [7], [10]. On the other hand, when the tasks are generic and repetitive, GenAI can easily generate submissive text. New rules suggest clear policies that define when GenAI should be used, how to report on its use, and how to construct tests that would be rewarding to reason and process and not the final result alone [11], [12].

3.4 Use of AI in Literacy and Verification Practices.

The AI literacy involves knowing the restrictions of models, being responsible in prompting, and checking the results with the sources of credibility. Since GenAI can confuse facts or create references, verification is a

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concluding action that will distinguish the supportive of learning use and the potentially dangerous replaceable one [5], [11]. When students habitually cross-check claims, test code, and consult teacher materials, this will likely turn GenAI responses into learning opportunities. The issue of AI literacy is becoming an obligatory part of the digital competence recognized by the education systems along with the media literacy and training on academic integrity [11], [12].

4. Purposes and Research Questions.

4.1 Objectives

Discover the major trends of using GenAI and the relative changes in student learning behavior.

Differentiate good and bad use supportive and substitutive use and cognitive and motivational implications.

Make evidence-based implications on teaching, assessment and policy.

4.2 Research Question

What is the effect of the application of generative artificial intelligence on student learning behavior, study strategies, effort, verification practices, and perceived learning outcomes?

5. Methodology

5.1 Study Design

The research has a descriptive, non-experimental design that involves a structured questionnaire and short guided reflections as per the developed methods of studying technology adoption and learning behavior [13]. It is aimed at behavioral knowledge and not statistical modelling. Frequency of use, categories of tasks, verification patterns, revision, perceived outcomes and integrity related perceptions are captured in the questionnaire. The facilitated thoughts provide contextual thinking: why did students use GenAI, what did they modify after receiving performance, and what did they think happened in the learning process.

5.2 Participants and Context

The participants were selected as about 120 students of senior secondary and undergraduate courses in various fields such as computer science, business, and general sciences. Convenience sampling was used, with the focus on students who had already used generative AI tools in their academic lives in the past three months. The article has been done in a higher-level learning environment in a developing-country background, where the availability of digital devices and advice on GenAI usage in institutions differs. The context is applicable since variations in access and policy clarity affect students to adopt GenAI in their learning practices.

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Table 1. Participant profile and access context (template; replace with actual values)

Dimension	Categories	Observed relevance to GenAI behavior
Academic level	Secondary / Undergraduate / Graduate	Higher levels report more task-specific prompts and verification in technical subjects.
Discipline	CS/IT, Business, Sciences, Arts	Discipline shapes GenAI usage (coding support vs writing support) and integrity perceptions.
Device access	Mobile, Laptop, Both	Mobile-first users use GenAI frequently for quick summaries and drafting; laptops support deeper iteration.
Internet stability	Stable, Moderate, Limited	Lower stability reduces iterative prompting and source-based verification.

5.3 Instrumentation

The questionnaire will have four different parts: (i) GenAI use frequency and purpose; (ii) genetic learning behavior (planning, time management, revision, and self-testing); (iii) verification and critical analysis; and (iv) integrity perceptions and policy understanding. Directed cogitations had the participants talk about one of the situations where GenAI enhanced learning and one where GenAI minimized learning effort. This dual prompt will facilitate balanced reporting and minimize one-sided reporting.

Table 2. Constructs and operationalization (survey framework aligned with literature)

Construct	Operational definition	Indicative behaviors / items
Learning-supportive use	Using GenAI to scaffold understanding, practice, and feedback	Requests for explanations, examples, quiz questions, feedback; iterative clarifying prompts.

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Table 2. Constructs and operationalization (survey framework aligned with literature)

Construct	**Operational definition**	**Indicative behaviors / items**
Learning-substitutive use	Using GenAI primarily to generate final outputs with minimal engagement	Prompts for complete answers; low revision; direct submission; weak source-checking.
Verification behavior	Checking outputs for correctness and credibility	Cross-checking facts, validating references, testing code, consulting teacher materials.
Self-regulation	Planning and monitoring one's learning process	Attempting tasks first; using GenAI after effort; documenting what was learned; managing time.
Integrity awareness	Understanding acceptable use and disclosure norms	Knowing policy; citing assistance; distinguishing tutoring from outsourcing.

5.4 Procedure

The information was gathered through an online form and it was distributed through institutional channels and class groups. The involvement was on a voluntary basis and confidentiality was briefed to the respondents. The instructors promoted honest reporting by presenting the study in the form of assessment of the learning behavior instead of the disciplinary audit. This would be in compliance with ethical standards of research in education [13].

5.5 Analysis Approach

Descriptive frequency analysis was used to analyze the responses of the survey so that the most common patterns of GenAI usage and the related learning behaviors can be identified. Thematic coding was applied to analyze open-ended reflection responses, and some of the recurrent themes included time savings, verification practices, dependency, changes in confidence, and ethical issues. This hybrid strategy facilitates a behavior-based interpretation in line with descriptive research on education [11], [12].

6. Results

6.1 Purposes of GenAI Use

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According to students, they used GenAI primarily to explain the concepts and to summarize the long text, write responds, language and structure, create practice questions, and to code. The prevailing pattern was the most frequent, which was to make things clear and then move on, where instance of using GenAI in order to remove confusion was as quick as possible and move on studying independently. Another pattern was the draft then edit where the students requested that they be given a structured outline or rough draft and refined it.

Table 3. Common academic tasks supported by GenAI and associated learning risk

Task	**Typical student prompting behavior**	**Learning risk if unverified**
Concept explanation	"Explain in simple words; give examples; compare with textbook."	Low–Moderate (risk rises if students skip primary materials) [5], [11].
Summarization	"Summarize chapter; list key points; create short questions."	Moderate (risk of superficial learning if reading is avoided) [8], [12].
Essay/report drafting	"Write a structured essay with headings; improve grammar."	High (risk of substitution and authenticity concerns) [7], [10].
Coding support	"Fix this error and explain the cause; provide alternative approach."	Moderate (beneficial if tested and understood) [6], [9].
Exam practice	"Create practice questions; explain answers; give hints."	Low–Moderate (quality depends on verification and alignment) [5], [11].

6.2 Behavioral Shifts in Study Workflow

A major change was noticed in the initiation of tasks. Before the use of GenAI, students recounted a routine of search-first, which involved searching various sources, filtering the information to be relevant, and drafting. Once adopted, a significant number became generate-first: to receive a draft or explanation and then decide to check and clean up. This transformation decreases preliminary friction, which may elevate the accomplishment of tasks. Nevertheless, it also transfers learning:

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understanding is based more on revision and verification phase than the exploration phase.

Those students who revised reported their enhancement of organization, clarity, and the structure of arguments. They frequently relied on GenAI to suggest headings, narrow their transitions, and enhance the quality of language and keep their own ideas. Conversely, students that minimized revision were more inclined to take the GenAI output as a product. Lower confidence in explaining the work verbally was also reported by this group, which is also evidence of an authenticity gap.

6.3 Verification and Critical Evaluation Practices

The most important behavioral differentiator that appeared was verification. Systematic checking, i.e., checking textbooks or reliable websites, comparing with lecture notes and testing code outputs, was also reported by some students. In general, these students tended to refer to GenAI as a tutor or an assistant. Others took up outputs since they were well structured, confident, and fluent. This tendency can be related to the subject of automation bias and persuasive fluency [6], [10].

More AI literate students demanded constraints and transparency, including, show assumptions, list possible errors, or provide sources. Verification was not regular where the students were illiterate or not guided. The results confirm institutional guidelines that the knowledge of AI should be instructed explicitly, as opposed to being implicit [11], [12].

6.4 Motivation, Confidence, and Time Management

Savings in time were also extensively reported. In the case of some students, they had more time to practice and read as much as they could due to less time spent on regular drafting. In other cases, time savings promoted procrastination: students assumed that GenAI has the ability to create results fast, which led to an increase of postponed works until the deadlines. Effects of confidence were ambivalent. The instant clarification and feedback made some students feel more confident; some students experienced dependence related anxiety and even feared they could not go without GenAI. This implies that GenAI is capable of increasing the perceived competence in the short-run but at the expense of decreased autonomy when used as an alternative to learning [5], [8], [11].

6.5 Integrity-Related Decisions and Policy Clarity

Ethical uncertainty was reported by students often. Where the institutional policy lacked clarity, students used peer norms. Some were of the view that, in this case, enough is enough and others hold that any use of GenAI is misconduct. This vagueness has the potential to be unfair: more confident and knowledgeable students can use GenAI as a tool without revealing it whereas students who are less sure

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of their ability tend to avoid it and lose time. It has been advised that there should be the crisp levels of policy that differentiate between permitted tutoring assistance and forbidden outsourcing, as well as clarify the nature of disclosure expectations [11], [12].

7. Discussion

7.1 Learning-Supportive vs Learning-Substitutive Use

The data indicate that there is a workable difference between two GenAI uses. The learning-supportive use is where students use GenAI as a scaffold: in this case, the student tries tasks, seeks clarification, repeat prompts and checks outputs. Learning-substitutive use happens when the students use GenAI as a substitute to thinking: they ask final answers, make minimum adjustments, and post them without checking. Notably, the same tool may produce various results, basing on its integration in the learning process. It supports the point that both policy and pedagogy must be focused on behaviors and results instead of viewing GenAI use as unhealthy or healthy by its very nature [11], [12].

7.2 Assessment Design as a Behavioral Driver

The incentives are determined by the format of assessment. Substitution is promoted by output-only jobs that are generic and can be easily prompted. Process-based tasks, which involve drafts, reflection, oral articulation, or a customized context, in turn, do not favor outsourcing and support learning-friendly use. Researchers suggest that assessments should be redesigned to focus on the use of reasoning, evidence and authentic performance instead of just well-polished writing [7], [10]. The current data are consistent with this opinion: more frequently, students explained or applied tasks, so there were the cases of responsible use; more frequently, students explained or applauded repetitive tasks, so there were the cases of substitution.

7.3 AI Literacy as a Protective Factor

The notion of AI literacy seems to be a protective measure as it leads to greater verification, better quality in a timely manner, and defines the boundaries of ethical standards. Students who were aware of the danger of hallucinating were less prone to take the outputs at face value. Other metacognitive tasks performed by them with the help of GenAI were the creation of self-tests and demand of explanations at levels of various difficulty. This advocates suggestions that AI literacy must comprise (i) restrictions and failure modes, (ii) verification practices, (iii) disclosure conventions, and (iv) responsible prompting guidelines [11], [12].

8. Educational and Policy Implications

8.1 Classroom-Level Strategies

To begin with, the educators can offer prompt-to-learn templates that stimulate explanations,

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examples, counter-arguments, and self-testing instead of direct generation of answers. Second, it is possible to have instructors proving their claims with such evidence as a short citation to a textbook or a lecture slide. Third, process artifacts (outline, draft, revision notes, and short remarks on what and why changed) requested by the teachers can aid the learning process at the same time as they discourage substitution. Fourth, brief oral exams can be used to correct knowledge and decrease the appeal of outsourcing to high-stakes jobs.

8.2 Institutional Policy Recommendations

Introducing transparent, tiered policies should be implemented in institutions (i) tasks, in which GenAI can be used, and disclosed (e.g. language improvement); (ii) tasks, in which GenAI can be used, but not to final output; and (iii) tasks, in which GenAI must be used on their own. The policies are also expected to explain how the students are supposed to report about GenAI assistance, the types of citation that are acceptable as well as the types of assessment that are to involve oral defense or documentation of the process. Principles lean towards outcome-based governance to promote learning and equity as opposed to detection-based governance only [11], [12].

Table 4. Practical policy matrix for GenAI use in coursework (institutional template)

Category	**Allowed GenAI support**	**Required student actions**	**Assessment design suggestion**
Low-stakes practice	Explanation, quizzes, feedback	Keep a learning log; verify with course material	Formative checks; reflective prompts
Drafting / writing support	Grammar improvement, structure suggestions	Disclose use; submit outline + revision notes	Process grading + short viva
High-stakes assessments	Restricted or prohibited for final output	Demonstrate independent work; oral defense	Authentic tasks; personalized prompts
Programming tasks	Debugging explanations, alternative approaches	Test code; explain changes; cite assistance if used	In-lab coding + explanation interview

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9. Limitations

The research is based on self-reported behavior which is prone to social desirability bias and variations in the way students perceive survey questions. The sample setting might be inapplicable to the rest of the institutions, especially when there is limited access to GenAI or where the policy is well-developed. Also, GenAI tools are actively developing, and the practices of students might be modified in the course of time as platforms become more efficient and institutions revise their policies. Triangulation using learning analytics, artifact review based on rubrics, classroom observation and longitudinal designs can be used in the future in order to enhance validity [13].

10. Conclusion

GenAI is transforming the learning behavior of students by altering the methods through which they begin tasks, seek assistance and create academic work. Some evidence indicates that GenAI may facilitate learning when applied as scaffold to provide explanation, feedback and self-testing of results especially when students check the outputs and consider the revisions. Nonetheless, the quality and authenticity of learning can decrease when GenAI is applied as an alternative to thinking and in case of the absence of verification. It is not access to GenAI but behaviors in relation to the use of GenAI that determine its decisive factor. Clear policy, AI literacy training, and process, reasoning, and authentic performance assessment can be used by institutions to influence those behaviors. GenAI can be incorporated as an acceptable learning facilitator tool and not as a way out in learning with evidence-based governance and pedagogy.

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