Friend or Foe? The Impact of Generative AI on Student Academic Motivation

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Abstract

As generative artificial intelligence (genAI) tools become increasingly integrated into higher education, their impact on students is still disputed. Grounded in Self-Determination Theory, this study investigated how genAI related autonomy, competence, and relatedness influence intrinsic motivation among undergraduate students in Ontario. A total of 114 participants completed measures assessing their psychological needs in relation to their experiences with genAI, as well as measures assessing their academic motivation. Regression analyses revealed that perceived autonomy significantly predicted intrinsic motivation across the full sample, while perceived competence emerged as the strongest predictor among frequent genAI users. Relatedness did not significantly predict motivation in either case. These findings suggest that freedom and perceived skill in using genAI tools may play a role in shaping students' motivational engagement. Implications of this study align with previous research suggesting a need for clear AI guidelines beyond strict prohibition, competency-based AI training, and open dialogue between all stakeholders to foster ethical and motivationally supportive use of genAI in academic settings.

Introduction

Artificial intelligence (AI) has advanced rapidly over the past decade, transforming various sectors and industries, including healthcare, media, finance, and, notably, education (Littman et al., 2021). AI in education is reshaping learning environments by enabling personalized instruction and enhancing educational outcomes for students while also relieving teachers of repetitive, time-consuming tasks like grading (Chan & Hu, 2023). Despite this, there is significant polarization among these groups regarding its usage (Petricini, Wu, & Zipf, 2023). As AI continues to develop at an unprecedented rate, outpacing previous estimations and growing exponentially (Littman et al., 2021), engaging in open and well-informed discussions about its implications on education becomes increasingly important. As such, our paper seeks to illuminate the relationship between Ontario students' perception of generative AI (genAI) and their academic motivation.

While lacking a universal definition, AI in this paper is defined as the simulation of human intelligence in machines to enable learning, reasoning, and self-improvement. The integration of artificial intelligence into educational contexts initially emerged from research institutions focused on advancing specialized, domain-specific applications of the technology (Kahn & Winters, 2021).

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Recently, the increasing popularity of genAI tools like ChatGPT have sparked considerable interest among researchers regarding its impact on student motivation. For instance, Bandura's Self-Efficacy Theory (1977) highlights the importance of believing in one's ability to succeed. GenAI can play a pivotal role in this context by providing individualized and interactive educational learning, as well as immediate, tailored feedback for problem-solving activities (Chiu, 2024; Chan & Hu, 2023). This support can enhance students' self-efficacy while simultaneously pointing out potential areas for improvement, ultimately building their academic confidence and fostering persistence through personalized, real-time guidance (Halkiopoulos & Gkintoni, 2024).

Similarly, Self-Determination Theory (SDT) emphasizes the importance of fulfilling three basic psychological needs to foster motivation: autonomy (feeling in control of one's actions), competence (feeling effective and capable), and relatedness (feeling connected to others) (Deci & Ryan, 2000). AI supports these needs by enabling autonomy through self-paced learning (Holmes et al., 2019), providing adaptive feedback to enhance competence (Chiu, 2024), and acting as supportive learning companions, which bolsters relatedness (Zawacki-Richter et al., 2019). By addressing these core needs, genAI has the potential to nurture intrinsic motivation, encouraging students to engage more deeply in their learning.

GenAI tools like ChatGPT are remarkably flexible, designed to adapt dynamically to user prompts, producing various outputs in textual, auditory, or visual formats (Feuerriegel et al., 2023). Though it lacks a genuine understanding of its responses and data sources, it can mimic human reasoning and creativity in increasingly complex ways (Feuerriegel et al., 2023). Students' recent unprecedented access to these powerful tools allows for the seamless utilization of genAI into their daily academic routines, assisting them with a variety of tasks, such as guidance in studying, problem-solving, content generation, data analysis, writing, research, critical thinking, and more (Lund & Wang, 2023).

While research is still in its early stages, studies suggest that genAI can have both positive and negative effects on student motivation. On the one hand, genAI use can enhance motivation by providing personalized learning experiences, improving engagement, and making complex tasks more manageable (Chiu, 2024; Halkiopoulos & Gkintoni, 2024). On the other hand, there are concerns from students, professors, and researchers that over-reliance on genAI could lead to decreased critical thinking skills and reduced motivation to engage in learning independently (Chan, 2023; Chan & Hu, 2023; Petricini, Wu, & Zipf., 2023). This dual impact highlights the urgent need to improve its implementation while mitigating risks. Consequently, researchers have identified the following factors that are critical for the successful integration of genAI into education:

1. ***AI Literacy:*** Both students and professors should have a foundational understanding of AI, covering essential topics like its applications, limitations, and ethical considerations (Chan & Hu, 2023; Milicevic et al., 2024; Ofosu-Ampong, 2024).
2. ***Clear Guidelines and Policies:*** Institutions should establish and regularly update guidelines for AI use, informed by ongoing student feedback and perceptions (Almasri, 2024; Chan & Hu, 2023; Ofosu-Ampong, 2024; Wang et al., 2023).
3. ***Supportive Academic Environment*:** Creating supportive and inclusive learning environments is crucial for fostering AI acceptance and encouraging open exploration of

AI's applications and ethical implications (Wang et al., 2023; Chan, 2023; Miller, 2024; Ofosu-Ampong, 2024).

Despite these critical factors being identified, only a handful of universities have adopted policies on genAI, with fewer than one-third of top institutions implementing specific guidelines (Xiao et al., 2023). Universities that do address it tend to embrace genAI as a valuable educational tool, yet overall, guidance remains sparse, leaving many students uncertain about its proper use (Petricini, Wu, & Zipf., 2023). This lack of structured policy raises the risk of misuse and academic integrity issues, underscoring the need for clearer institutional policies to effectively integrate genAI tools into academia (Xiao et al., 2023).

Gaps in the research

Given the rate of technological change, the research on genAI has numerous identifiable gaps in regard to education. First, while the literature suggests that institutions have a wide range of responses to genAI– from outright bans, to not responding, to advocating its usage– (Xiao et al., 2023), there is limited examination of how students feel about these restrictions. Second, the importance of AI literacy is frequently stressed among researchers (Ofosu-Ampong, 2024), but less is known about whether students are keeping up with the technology and integrating it seamlessly into their education. Third, the literature suggests that genAI is a polarizing topic among students and faculty (Almasri, 2024), but to what extent this polarization is causing measurable harm to students' sense of connection is not well understood. Given its increasingly common usage (Yachouh, Maqbool, & Rao, 2024), it may just as well be a way for students to bond over or communicate more efficiently in group projects. Finally, while there is evidence that genAI can aid intrinsic motivation among students under the right conditions (Halkiopoulos & Gkintoni, 2024), it remains to be seen whether these conditions are met in Ontario universities.

For the present study, we address these gaps by exploring student perceptions of genAI in Ontario and the impact these perceptions have on students' intrinsic motivation. Our research questions will be framed using Self-Determination Theory (SDT), which forms the backbone of our study and aligns well with the fundamental elements for successful genAI integration: AI literacy, clear guidelines, and a sense of open communication among students are highly relevant within the SDT framework. AI literacy directly correlates with feelings of competence or mastery, interpretation of policy and restriction relates to autonomy, and the ability to connect with other students when using genAI fosters a sense of relatedness.

Purpose

The rapid integration of genAI tools into academic environments necessitates a deeper understanding of their impacts on student motivation and educational outcomes. Given intrinsic motivation's established role in predicting student engagement and academic achievement (Ryan & Deci, 2017), this study explores how the three basic psychological needs– autonomy, competence, and relatedness– associated with genAI usage influence intrinsic motivation among undergraduate students. Grounded in SDT, this research contributes to educational psychology and technology-enhanced learning by extending theoretical insights into motivation within contemporary educational contexts.

Examining the ethical dimension of genAI and the feelings associated with its use, this research provides practical implications for policy development and pedagogical strategies. Ultimately, our findings aim to guide institutions in ethically and effectively integrating genAI tools to optimize student motivation and improve educational outcomes.

Hypotheses

Hypothesis 1:

We hypothesize that higher feelings of competence in genAI usage will be positively associated with increased intrinsic academic motivation. According to Self-Determination Theory (SDT), the feeling of competence—an individual's belief in their ability to effectively perform tasks—fosters intrinsic motivation (Ryan & Deci, 2017). When students feel skilled at using AI tools, they may approach academic challenges with greater confidence, leading to increased engagement and enjoyment. Moreover, the pursuit of mastery has been shown to enhance intrinsic motivation (Rawsthorne & Elliot, 1999). Thus, we hypothesize that a stronger sense of competence in AI usage will enhance students' intrinsic motivation toward their academic tasks, encouraging them to persevere and find greater satisfaction in their educational pursuits.

Hypothesis 2:

Greater feelings of autonomy in genAI usage will be positively associated with intrinsic motivation. SDT posits that autonomy—feeling a sense of volition and control over one's actions—is a key driver of intrinsic motivation (Deci & Ryan, 2000). When students have the freedom to explore and utilize AI tools on their own terms, they may experience a heightened sense of self-direction. This autonomy, in turn, fosters a deeper connection to the learning process and increases intrinsic motivation towards academic tasks. Research has consistently shown that students who feel autonomous in their learning environments demonstrate greater self-efficacy, engagement, and perceived task value (Garcia & Pintrich, 1996). Thus, we hypothesize that allowing students more control over their AI usage will enhance their intrinsic motivation, leading to more meaningful and fulfilling academic experiences.

Exploratory Focus:

Due to genAI usage being a primarily solo activity, we do not offer any specific hypotheses about its role in fostering or impeding students' academic motivation. However, it is still relevant enough to include amongst our measures, and we plan to examine any patterns in the data that may emerge in the data that might help inform future research.

Method

Participants

Our study received 176 responses recruited through Instagram, posters, and McMaster's SONA system. Out of the 176 responses, we excluded 49 due to failing attention checks, 4 students due to lack of consent, 1 student due to a lack of proficiency in reading English, and 8 individuals who were not undergraduate students. The final sample consisted of 114 participants, primarily from McMaster University, enrolled in the Social Sciences.

Table 1. Participant Demographics

	M (SD)	%	n
Age	20.48	–	114
Gender	–		
Male	–	19.3	22
Female	–	76.3	87
Non-Binary	–	2.6	3
Transgender	–	.9	1
Prefer not to say	–	.9	1
University	–		
McMaster	–	95.6	109
Guelph	–	2.6	3
Brock	–	.9	1
Laurentian	–	.9	1
Program			
Arts and Humanities	–	2.6	3
Social Sciences	–	63.2	72
Natural Sciences	–	10.5	12
Engineering	–	7.9	9
Mathematics and Computer science	–	5.3	6
Business and Management	–	1.8	2
Other	–	8.8	10
Year			
First	–	4.4	5
Second	–	28.9	33
Third	–	35.1	40
Fourth	–	25.4	29
Fifth or beyond	–	6.1	7

Procedure and Measures

After recruitment, the participants were first directed to Qualtrics, an online survey platform, where they were asked to give informed consent to participate. They then completed the survey online through Qualtrics, taking approximately 15-20 minutes to complete. Participants received course credit if recruited through SONA; otherwise, no compensation was provided. The study procedures and measures were approved through the McMaster University Research Ethics Board.

Given the novelty of our research focus, we adapted questions from the Basic Psychological Need Satisfaction Scale (Deci & Ryan, 2000; Gagné, 2003) and the Basic Psychological Need Satisfaction at Work Scale (Deci & Ryan, 2000; Deci et al., 2001; Ilardi et al., 1993; Kasser et al., 1992).

Items were reworded and tailored to reflect participants' experiences and perceptions using genAI tools. Each construct-specific scale consists of questions rated on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree), with higher scores indicating greater perceptions of autonomy, competence, or relatedness in the context of genAI usage. Composite scores for each construct were calculated by averaging responses to the corresponding survey items. Internal consistency was evaluated using Cronbach's alpha.

Autonomy

Autonomy was measured using an 8-item scale that assessed students' perceived choice, freedom, and institutional support in their use of generative AI. Items captured whether students felt they could independently decide how to use AI in their studies. For example, one item stated, "I can decide how I use generative AI in my studies." The scale also explored whether students felt free to explore AI's applications without fear of negative consequences, and whether they believed their institution trusted them to make these decisions. To account for perceptions of constraint or concealment, three items were reverse-coded. One of these stated, "I feel I need to keep my use of generative AI private from professors or peers." Internal consistency was low but acceptable for exploratory research (Cronbach's $\alpha = .607$), with item-total correlations ranging from .117 to .477.

Competence

Competence was assessed using a 12-item scale that measured students' confidence, skills, and knowledge related to using genAI in academic work. Items addressed students' feelings of proficiency in terms of their genAI usage, as reflected in statements like "My ability to effectively integrate generative AI into my studies is impressive." The scale also assessed students' capacity for critical evaluation, such as "When generative AI gives me an answer, I can critically assess its accuracy." In addition, items captured students' awareness of more advanced methods, including "I am aware of advanced techniques in using generative AI that go beyond basic usage." The scale showed excellent internal consistency (Cronbach's $\alpha = .885$), with item-total correlations ranging from .200 to .813, indicating strong internal cohesion and a likely unidimensional structure.

Relatedness

Relatedness was measured using a 10-item scale focused on students' sense of connection to peers and the broader social climate surrounding AI use. Items examined whether students felt comfortable using AI in collaborative academic contexts and whether genAI fostered a sense of belonging. For instance, one item stated, "AI makes it easier to work with classmates or communicate ideas in group work." Another item reflected the broadly unifying aspect of AI use: "Using generative AI makes me feel like I'm part of a forward-thinking community." Two reverse-scored items that captured tendencies to conceal AI use or feel socially disconnected were removed due to negative item-total correlations. After their removal, the resulting 8-item scale showed improved reliability (Cronbach's $\alpha = .674$), and retained items consistently reflected social and collaborative themes.

Academic Motivation

To measure academic motivation, we administered the 14-item Short Academic Motivation Scale (SAMS; Kotera, Conway & Green, 2020). This scale captures a range of motivational orientations, including intrinsic motivation (e.g., "For the pleasure that I experience while I am surpassing myself in one of my personal accomplishments"), extrinsic motivation (e.g., "In order to have a better salary later on"), and amotivation (e.g., "I don't know; I can't understand what I am doing in school").

Although only intrinsic motivation was used in the final analyses, all three subscales were assessed for internal consistency. The 6-item intrinsic motivation subscale showed strong internal reliability (Cronbach's $\alpha = .863$). The 6-item extrinsic motivation subscale showed acceptable internal reliability ($\alpha = .742$), as did the 2-item amotivation subscale ($\alpha = .720$).

Analysis

An a priori power analysis was conducted using G*Power to determine the minimum sample size needed for detecting medium effect sizes ($f^2 = .15$) with three predictors, $\alpha = .05$, and desired power of .80. This analysis indicated a minimum required sample of 77 participants. Our final sample of 114 participants exceeded this requirement, providing adequate statistical power. Prior to analysis, data was screened for quality and completeness.

Pearson's correlation coefficients were computed to examine relationships between AI-related autonomy, competence, relatedness, and motivation variables. Multiple regression models were employed to examine the predictive power of AI-related autonomy, competence, and relatedness on intrinsic and extrinsic motivation. Standardized beta coefficients were used to assess the relative contribution of each predictor, and model fit was evaluated using R^2 values.

Exploratory analyses were conducted to examine the influence of AI usage frequency on the relationships between our key variables. Participants were categorized based on their reported frequency of AI use, and separate regression models were tested for different usage groups to determine whether the relationships between AI-related psychological needs and motivation varied by usage pattern.

All analyses were conducted using SPSS version 28.0. Ethical approval for this study was obtained from the McMaster University Research Ethics Board, and all participants provided informed consent before completing the survey.

Results

Descriptive statistics were calculated for all key variables, which can be viewed in Table 2. Among the constructs, autonomy had the lowest average score (*M* = 3.62, *SD* = 0.82), suggesting that students generally perceive limited freedom or support in how they can use genAI in their studies. In contrast, students reported relatively high average levels of competence (*M* = 4.58, *SD* = 1.07) which indicates a strong sense of skill and confidence, though this feeling of mastery varies significantly. Relatedness showed a moderate mean score (*M* = 4.03, *SD* = 0.75), reflecting some degree of social connection or shared understanding around AI use among peers. Mean intrinsic motivation was relatively high (M = 4.92, SD = 1.17), suggesting that students generally feel intrinsically motivated.

Table 2

Descriptive Statistics for Measures

	n	Range	Mean	SD
Autonomy	114	3.88	3.62	.82
Competence	114	4.67	4.58	1.07
Relatedness	114	3.30	4.03	.75
Intrinsic Motivation	114	6.00	4.92	1.17

Bivariate Correlations

Pearson correlation analyses were conducted to examine the relationships between the key measures. As predicted, autonomy was significantly positively correlated with intrinsic motivation (r = .27, p = .004) and was also associated with competence (r = .23, p = .015) and relatedness (r = .37, p < .001). Competence was strongly related to relatedness (r = .52, p < .001) but was not significantly correlated with either intrinsic or extrinsic motivation.

Relatedness did not significantly correlate with either intrinsic or extrinsic motivation. However, extrinsic and intrinsic motivation were significantly positively correlated (r = .50, p < .001), suggesting that students who are motivated by internal interest may also report being motivated by external factors. No significant associations emerged between autonomy or competence and extrinsic motivation (ps > .05).

Multiple Regression Analysis

A multiple regression analysis was conducted to examine whether autonomy, competence, and relatedness predicted intrinsic motivation across the full sample (*N* = 114). The overall regression model was significant, *F*(3, 110) = 3.21, *p* = .026, accounting for 8.1% of the variance in intrinsic motivation (R^2 = .081, Adjusted R^2 = .056). Among the predictors, autonomy emerged as a significant positive predictor, *b* = 0.367, *SE* = 0.140, *β* = .26, *t*(110) = 2.61, *p* = .010, indicating that students who perceived greater freedom in their use of AI reported higher intrinsic motivation. In contrast, competence was not a significant predictor, $b = 0.129$, $SE = 0.116$, $\beta = .118$, $t(110) = 1.10$, $p = .272$. Relatedness was also non-significant, $b = –0.080$, $SE = 0.174$, $\beta = –.05$, $t(110) = –0.46$, $p = .646$.

These findings suggest that perceived control over AI use plays a more central role in intrinsic motivation than students' self-assessed skill or sense of peer connection, particularly when examining a mixed group that includes both users and non-users.

Exploratory Analysis

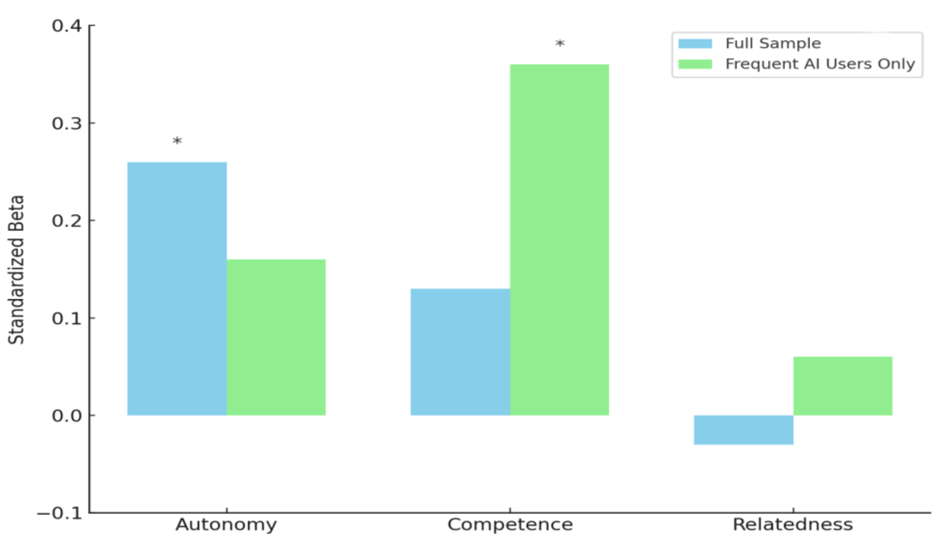
An exploratory regression was conducted among students who reported using generative AI multiple times per week ($n = 64$). This model remained statistically significant, $F(3, 60) = 4.87$, $p = .004$, with a notably higher explanatory power ($R^2 = .196$, Adjusted $R^2 = .155$). In this model, autonomy was no longer a significant predictor, $b = 0.225$, $SE = 0.183$, $\beta = .16$, $t(60) = 1.23$, $p = .222$. Although autonomy was no longer statistically significant in this model, the positive direction of the effect ($b = 0.225$) may still warrant further study. Competence was the only significant predictor, $b = 0.690$, $SE = 0.229$, $\beta = .36$, $t(60) = 3.02$, $p = .004$, suggesting that students who felt more skilled and confident in using AI reported greater intrinsic motivation. Relatedness remained a non-significant predictor, $b = 0.099$, $SE = 0.234$, $\beta = –.06$, $t(60) = 0.43$, $p = .673$.

Model Comparison and Interpretation

These results reveal a shift in predictive strength depending on students' prior AI experience (Figure 1). When considering the full sample, perceived autonomy appears to drive intrinsic motivation; potentially because having the *option* to explore AI, regardless of actual use, enhances motivational orientation. However, within the subset of actual AI users, competence emerged as the key predictor, underscoring the importance of perceived skill and efficacy in fostering motivation once students are actively engaging with the technology.

Figure 1

Standardized Beta Coefficients Predicting Intrinsic Motivation from Autonomy, Competence, and Relatedness



Discussion

The primary aim of this study was to provide clarity into a majorly understudied area within educational psychology: the impact of genAI tools on student academic motivation. Self-determination theory provides a robust and comprehensive framework from which we can begin to understand this impact more directly. Our findings suggest that the integration of genAI into learning environments has context-dependent effects on motivation, particularly in regard to frequency of usage, which warrants a nuanced look into the implications of this study.

Confirming our hypothesis, autonomy played a small but significant role as a predictor of students' intrinsic academic motivation. This aligns with prior research in SDT suggesting that autonomy can foster intrinsic motivation among students and anchor learning in personal meaning rather than external control (Kusurkar et al., 2011). Importantly, autonomy was the lowest score out of the three constructs, and many students feared that the use of genAI would result in academic penalties. This is not surprising, as academia is still skeptical of the tool being used unethically, prompting educators and institutions to default towards restriction (Xiao et al. 2023). However, the results indicate that such restriction might have unintended negative effects, isolating them from using tools that they see as potentially valuable or necessary. Students may be anxiously aware of the mounting value placed on AI-related skills and competencies in the job market.

In our exploratory analysis examining frequent AI users, we found that autonomy no longer became a statistically significant predictor of intrinsic motivation. This means that once an individual regularly uses genAI, the feeling of restriction no longer negatively impacts their motivation. This shift may reflect a process of cognitive dissonance reduction (Festinger, 1957), wherein students reconcile their continued use of genAI with institutional restrictions through rationalizations such as the tool’s utility, its future relevance, or its usage among peers. In any case, the motivational cost of restriction appears to diminish over time for frequent users, suggesting that adaptive psychological mechanisms may play a role in buffering the demotivating effects of perceived external control.

Contrary to our second hypothesis, competence did not play a significant role in predicting intrinsic motivation among the student body. This result is unexpected given the potential of genAI to aid the learning process and foster motivation when the need for competency is met (Chiu, 2024). Evidently, the mere feeling of competency in using genAI does not necessarily boost intrinsic motivation above normative levels, which could be explained by the discrepancy between perceived competence and actual competence. It may be that students think they are using the tool effectively to aid their studies, but lack the genuine depth of understanding, strategic thinking, or even metacognitive reflection necessary to harness the motivational potential of tools whose value emerges only through disciplined exploration or structured guidance.

Intriguingly, among students who used genAI frequently, competence became a moderately strong predictor of intrinsic motivation. These findings suggest two things: first, students can be highly intrinsically motivated in academic tasks as long as they feel they can use the tool effectively. However, this does not necessarily connote that the tool is in fact being used in ways that truly enhance deep learning. Secondly, some students report frequent use of AI tools despite lacking confidence in their ability to use them effectively which in turn correlates with low levels of intrinsic motivation. This pattern may indicate that, even in restrictive academic environments, students are still knowingly engaging with AI in ways that are suboptimal or even inappropriate.

Relatedness was not correlated with intrinsic motivation; likely because using genAI is an individual rather than a social experience. It may be that we examined this construct from the wrong perspective. Perhaps what should be measured is the extent to which the student feels socially connected or personally understood by their AI learning system, which is what research suggests leads to higher motivation and improved learning outcomes (Ebadi & Amini, 2022). As genAI continues to become more personalized to each individual, this aspect of relatedness might be increasingly relevant to student motivation.

Implications

While this data is not enough to make any firm conclusions on its own, it echoes the existing concerns already present within the literature. GenAI is not going away any time soon and will continue to get more advanced and integrated into society over time (Littman et al., 2021). Concerns over its misuse are indeed warranted; but much like how the prohibition of alcohol forced the industry underground (Hall, 2010), or abstinence only education increases risky sexual behavior (Trenholm et al., 2008), simply banning genAI altogether may cause similar types of problems. Increasing numbers of students are leveraging genAI tools at McMaster (Yachouh, Maqbool, & Rao, 2024), but if they are afraid to ask questions regarding proper usage due to restriction, then their AI competency suffers, potentially lowering intrinsic motivation and harming learning outcomes. Further, the student might be motivated to gain competency in the wrong direction by learning how to avoid AI detection through prompt engineering, minor edits to generated content (Fishchuk & Braun, 2024) and using AI tools designed to bypass detection; tools that are notably marketed directly to students (Perkins et al., 2024). Ultimately, this creates an anxiety fueled arms race that unintentionally sidesteps the very purpose of education. Prohibitory restrictions could be substituted for clear, universalized guidelines designed to foster an open, stress-free environment where students and educators can discuss these challenging times in a safe space.

Reducing restriction might not be particularly beneficial on its own. GenAI tools are increasingly complex, and the boundary between productive usage and excessive cognitive offloading is by no means self-evident. It is not only educators who are concerned about this; students themselves have expressed concerns that their usage of genAI might be adversely affecting their actual learning and retention (Yachouh, Maqbool, & Rao, 2024). Any academic tool holds the potential for misuse, but responses to this fact have historically been centered around education rather than dismissal. In line with this, most researchers emphatically support AI literacy training among both students and staff (Barrett & Pack, 2023; Chan, 2023; Chan & Hu, 2023 Milicevic et al., 2024; Ofosu-Ampong, 2023; Țală et al., 2024; Wang et al., 2023).

Literacy and communication alone won't eliminate misuse of the tool, but there are other strategies beyond restriction that could alleviate this concern. Incorporating experiential or project-based learning, or new forms of assessment that are conducted in person, like oral exams, or even incorporating critical assessment of AI-generated outputs into the assignment itself, are cited as possible solutions (Evangelista, 2025).

Assessments that use structured frameworks to evaluate students' metacognitive reflections, such as key decisions made or challenges encountered during drafting encourage critical thinking and self-reliance, while potentially reducing the appeal of external tools (Ratto Parks, 2023). Although misuse will likely continue regardless of any strategies employed, such strategies still provide the best possible path towards successful genAI integration, reducing its harms and maximizing its benefits.

Limitations

While this study offers timely insight into the motivational impact of genAI tools in academic settings, several limitations should be considered when interpreting the findings. Most notably, the cross-sectional design prevents any conclusions about causality; we can identify associations, but not directional effects. Given the emerging nature of this research area, it is essential to interpret the results cautiously and in the context of other research until they can be replicated in future studies.

Another important consideration is the sample itself. The participants were predominantly Social Science students from McMaster University, which limits the generalizability of the findings across different academic disciplines and institutions. Moreover, because the sample was non-randomized and based on voluntary participation, there is a high risk of selection bias, which may have skewed the data toward students who are either particularly interested in or already engaged with AI technologies.

Finally, the study relied on self-report measures, which can be vulnerable to various forms of response bias. Social desirability, self-justification, and inaccurate recall may have influenced participants' responses, especially given the ambiguity surrounding what constitutes effective uses of genAI in academic contexts.

Future research directions

While perceived autonomy and competence in using genAI might be correlated with intrinsic motivation, further research could look into whether it actually directly impacts the ability to learn information and create high-quality academic work. While perceived competence is an important aspect of SDT, we recommend future research to include measures of actual competence in using AI to gain clarity as to what level of AI literacy students currently have beyond mere subjective opinion. In addition to this, future research could instigate a longitudinal design that can more accurately assess the impact of adopting genAI tools into the learning process.

Conclusion

The debate regarding genAI's application in higher education is far from settled. Yet, the present study does seem to indicate that restricting its usage altogether may have a negative impact on a student's academic motivation insofar as it reduces student autonomy and competence. Further, this restriction could limit students' ability to attain AI-related competency, which is an increasingly important skill as AI continues to percolate throughout various sectors. Students can be afforded the opportunity to engage with these tools ethically and think critically about their application in academic work rather than rely on them as substitutes for thought.

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