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Exploring ethical concerns and affordances of generative AI in higher education: Perspectives of underserved students

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Abstract

The study explores the ethical concerns and the affordances of generative artificial intelligence (GenAI) in higher education from the perspectives of underserved students. Data were collected through a survey of 77 students in a public university with predominantly underserved students in the United States. Informed by the five principles of AI ethics and technology affordance theory, the study employed a mixed-methods approach. Qualitative analysis of the narrative data revealed six themes: utility affordances, value affordances, user behavior, AI use outcomes, the contingency of ethical AI use, and a pessimistic view of ethical AI use, suggesting that ethical considerations in GenAI use depended on user perspectives. Furthermore, quantitative analysis indicated that student perceptions of the ethical use of GenAI varied by their demographic and socioeconomic background. The study also revealed nuances of the digital divide in AI. The study contributes to the literature by proposing an integrated model of ethical GenAI use and offers practical implications for promoting effective and ethical use of GenAI in higher education.

Keywords: artificial intelligence, genAI, ethics, affordance, digital divide, underserved students, higher education

Introduction

The rapid advancement of artificial intelligence (AI) has significantly transformed our society. As a subset of AI models, generative AI (GenAI) can generate seemingly new, meaningful content such as text, images, or audio based on the training data (Feuerriegel et al., 2024). Commonly used GenAI platforms include ChatGPT, Gemini, and Copilot for text, as well as Dall-E and Midjourney for images, among others. With its power to produce various types of content and exhibit human-like capabilities, GenAI has proliferated in our work and education, sparking both enthusiasm and concerns among many.

In higher education, debates about GenAI revolve around issues such as academic integrity, skill development, and the balance between leveraging AI for innovation and creativity while preventing overreliance on technology (Nguyen et al., 2024; Zhai et al., 2024). On the one hand, research has shown that GenAI benefits student learning such as providing personalized learning and automated feedback (Chen, 2022) and enhancing programming self-efficacy and learner motivation (Yilmaz & Yilmaz, 2023). On the other hand, scholars have warned us about GenAI misuse (e.g., plagiarism) (Terwiesch, 2023) and its unintended consequences on human cognition and skills (Bowen & Watson, 2024). Despite the debates, educators and scholars share the concern that GenAI integration in higher education has posed ethical challenges, including key ethical dimensions related to accountability, human oversight, transparency, and inclusiveness (Dabis & Csáki, 2024; Deng & Joshi, 2024). University students have also expressed concerns about the accuracy, privacy, and ethical issues related to AI (Chan & Hu, 2023) and wanted clear institutional support and guidance on how to use AI appropriately (Tierney et al., 2025). Ethical AI should also concern large-scale ethical issues around biases in training data and AI algorithm development as well as organizational and environmental impacts (Moussawi et al., 2024).

The paradoxical impacts of GenAI on underserved students will be profound. In the United States, *underserved students* are defined as those who possess at least one of the following characteristics: (1) racial or ethnic minority; (2) low household income; or (3) first generation in college (i.e., highest parental education level is high school or less) (ACT Inc., 2014). Unfortunately, higher education institutions serving a large population of underserved students still face challenges in closing the digital divide and achieving the digital literacy of its underserved students (Deng & El Hag, 2024). In the era of AI, digital divide may be exacerbated or reduced depending on how the technology is deployed and accessed. One argument is that underserved students may lack the educational infrastructure and skills to effectively engage with the rapidly evolving AI technologies. A counterargument is that, by providing personalized learning experiences, AI can help level the educational playing field and bridge the digital divide. For example, having experimented with the free version of ChatGPT in university-level courses, students from diverse backgrounds found that GenAI was helpful with their learning tasks (Sun & Deng, 2025).

Researchers have started to examine factors that contribute to the AI experiences of individuals from various communities and found that individual factors (e.g., women and the elderly) and socioeconomic background (e.g., low income) are significantly associated with lower digital confidence with understanding and using digital technologies such as AI (Bentley et al., 2024). Since underserved university students share similar characteristics such as low socioeconomic status, it is important to understand how this marginalized population can utilize AI ethically and responsibly to minimize the risk of being left behind in an AI-driven society. Nonetheless, we still have limited knowledge about the effective use and unintended consequences of using GenAI among underserved university students.

To address the research gap, this study explores ethical concerns and the affordances of GenAI use in higher education from the perspectives of underserved students. Specifically, the study addresses three research questions (RQs):

- RQ1: What ethical considerations arise from underserved students' use of GenAI?
- RQ2: What are the affordances of GenAI in education?
- RQ3: Do underserved students' perceptions of the ethical use of GenAI vary by their demographic and socioeconomic background?

To answer the research questions, this study employs a mixed-methods approach involving both qualitative and quantitative analyses that complement each other and potentially provide a richer exploration of the linkages across variables (Mingers, 2001). RQ1 and RQ2 are addressed through qualitative analysis, while RQ3 is answered by quantitative analysis. This exploratory study is informed by research on the principles of ethical AI (Floridi & Cowls, 2022; Floridi et al., 2018; Jobin et al., 2019) and the technology affordance theory proposing that the realization of technology features depends on the users themselves (Faraj & Azad, 2012). User acceptance is essential to the successful uptake of technological innovations (Davis, 1989). In a learning environment, how students perceive a technological innovation such as GenAI can influence their willingness to utilize the technology in learning, and the same technology may have different affordances depending on the user and situation. That is, how AI is used and by whom will impact AI use for information seeking (Davis, 2020).

The research setting of the study is a minority-serving, urban public university in the United States. Data were collected through a survey of 77 students in the business college of the university, where most students come from underserved local communities with limited educational resources. This research setting helps enhance our understanding of ethical GenAI use from the perspective of underserved students.

The qualitative analysis of responses to an open-ended survey question revealed six themes related to ethical considerations and affordances of GenAI use in higher education. The quantitative analysis of the numerical survey data showed that student perceptions varied by their individual backgrounds. The study contributes to the literature through expanding technology affordances to the new technology of GenAI and revealing the multifaceted nature of ethical considerations for GenAI use. It also proposes an integrated model of ethical GenAI use that links the ethics principles in AI design with the utility and values affordances perceived by GenAI users. Finally, the study's focus on the GenAI use of underserved students has practical implications for promoting inclusive excellence in higher education.

The paper proceeds as follows: Section 2 reviews the literature on GenAI use in higher education and the digital divide experienced by underserved students, followed by explanations of the theoretical background—ethical AI principles and technology affordances. Section 3 describes the research setting, data collection, and participant characteristics. Section 4 reports the qualitative analysis and findings while Section 5 presents quantitative analysis and results. Section 6 discusses the findings, proposes an integrated model of ethical considerations for GenAI use, and highlights the study's theoretical contributions and practical implications. Finally, Section 7 concludes with a summary of key findings, study limitations, and suggestions for future research.

Literature review

GenAI use in higher education

Despite being a new technology publicly launched in November 2022, GenAI applications such as ChatGPT have been rapidly adopted by university students. A survey of approximately 1,600 students and over 1,000 faculty across more than 600 higher education institutions in the United States reported that 49% of students regularly used GenAI for academic tasks as of September 2023, with 75% of student AI users expressing the intent to continue using GenAI tools despite potential restrictions by their instructors or institutions, showing a much higher adoption rate than that of faculty (22%) (Shaw et al., 2023). The survey respondents came from a variety of institutions including public four-year colleges, private four-year colleges, community colleges, and trade or vocational schools. Respondents also varied in their backgrounds: 19% first-generation college students (FGCSs), 30% financial aid recipients, 38% employed while attending school, 53% White, 24% Black or African American, 21% Hispanic, and 8% Asian (Shaw et al., 2023).

Research has found positive impacts of GenAI on student learning in higher education. For example, students using ChatGPT in a computer programming course were rated higher in their computational thinking skills, programming self-efficacy, and motivation than the cohort who did not use ChatGPT (Yilmaz & Yilmaz, 2023). In a graduate-level instructional design course, students who utilized GenAI to facilitate learning reported significant personal and professional growth, including better time management, improved critical thinking, and a deeper understanding of instructional design principles (Wood & Moss, 2024). Moreover, a recent study found that students' motivation and ability to assess the credibility of GenAI-generated information were influenced by six factors: task salience, task verifiability, social pressure, trust in GenAI, domain knowledge, and time availability (Choi et al., 2025).

Despite the evidence of these positive impacts, studies have also identified negative effects of GenAI use on student learning. For example, a study of first-year students in a German university (Wecks et al., 2024) suggested that GenAI may hinder student learning: students using GenAI tools in writing case study essays scored lower on the exam than non-users and the negative effect was particularly detrimental to students with high learning potential. Similarly, a study of 54 participants recruited from several universities in the United States revealed that while the use of large language models (LLMs) such as ChatGPT brought initial benefits, participants using a LLM to write an essay performed worse than their counterparts who did not use the LLM initially but were allowed to use it in re-writing the essay, suggesting a negative impact of AI on the development of learning skills if introduced too early (Kosmyna et al., 2025). To achieve both immediate tool efficacy and lasting cognitive autonomy, the authors recommended delaying AI integration until learners have engaged in sufficient self-drive cognitive effort (Kosmyna et al., 2025).

Reflecting on both sides of the argument, scholars have suggested the duality of GenAI use in higher education. For example, a study in six Hong Kong universities revealed that students recognized the potential of GenAI for personalized learning support, writing and brainstorming assistance, and research and analysis capabilities, while they expressed concerns about GenAI's accuracy as well as about privacy and ethical issues, and the impact on personal development, career prospects, and societal values (Chan & Hu, 2023). Another study in the United Kingdom found similar evidence of both positive and negative student perspectives regarding AI in higher education (Tierney et al., 2025).

Digital divide and AI

Digital divide initially referred to socioeconomic disparities in physical access to computers and the Internet (Gunkel, 2003). Subsequently, researchers have extended the concept to describe differences in individual usage and user skills. One common term used by researchers is *digital competence*, defined as a combination of information, communication, content creation, and problem-solving skills (Ferrari, 2012). Despite advancements in access to information and communication technologies (ICT), disparities in ICT resource access, skills, and usage persist (van Deursen & van Dijk, 2019). Research into the underlying factors contributing to the digital divide has revealed individual and socioeconomic factors as the common causes, among which, four factors—income, education, race/ethnicity, and employment status—are closely related to the characteristics of underserved students (Deng & El Hag, 2024). In online education, underserved college students were found to be not only technologically disadvantaged but also encountering multifaceted barriers due to family responsibilities and employment obligations (Deng & Sun, 2022).

The digital divide problem experienced by underserved students becomes even more worrisome in the age of AI. As AI becomes more pervasive and rapidly integrated into various aspects of our daily lives—from workplaces to education—those without access to or understanding of these technologies risk being left at a significant disadvantage. Thus, the advancements of AI have given rise to a new type of divide—the AI divide—the widening gap between those who have the resources and capabilities to benefit from AI and those who do not (Dogra, 2025). The AI divide encompasses the disparity not only in access to AI technologies but also the ability to develop and benefit from these technologies.

Prior research has conceptualized the AI divide as a subdimension of the digital divide. For example, Carter et al. (2020) define the AI divide as "AI-related inequalities about access to AI (the first-level divide), the ability to use AI (the second-level divide), and the outcomes of AI engagement (the third-level divide)" at multiple levels—individual, institutional, and country—while emphasizing the significance of individuals' perceptions, beliefs, and AI attitudes (p. 259). A recent study by Wang et al. (2025) calls for attention to understanding the second-level divide in terms of users' AI knowledge and skills and the third-level divide in terms of user attitude toward AI in the rapidly increasing deployment of AI technologies.

Although the digital divide and the AI divide are closely related concepts, it is important to distinguish between them. The AI divide is a newer, more complex form that builds on the digital divide, specifically addressing unequal access to and understanding of advanced AI technologies, including the skills to develop, use, and critically engage with AI tools. It considers factors beyond basic access to technology, such as AI literacy, data, algorithms, and the ability to benefit from the opportunities that AI offers.

Ethical AI principles

GenAI includes a suite of technologies capable of producing new content based on existing data, advancing the adoption of ICT in organizations. With significant multimodal capabilities, GenAI spans the processing not only of human languages and computer code but also of images, videos, audio, and rich human-computer interactions (Feuerriegel et al., 2024). Prior studies have highlighted the importance of individual factors such as perceptions and cultural orientations in people's ethical behavior in using computer technologies in organizations (Lowry et al., 2014; Mingers & Walsham, 2010).

There is a debate about what constitutes "ethical AI." Organizations have launched a wide range of initiatives to establish ethical principles for the adoption of socially beneficial AI. Analyzing several of the highest-profile sets of ethical principles for AI, Floridi and colleagues (Floridi & Cowls, 2022; Floridi et al., 2018) assessed whether these principles converge upon a set of agreed-upon principles, or diverge, with significant disagreement over what constitutes "ethical AI." Their analysis revealed an overarching framework consisting of five core principles, four of which are commonly used in bioethics—beneficence, non-maleficence, autonomy, and justice—and a new principle of explicability. First, *beneficence* refers to promoting well-being, preserving dignity, and sustaining the planet, ensuring that AI technologies benefit and empower as many people as possible. Second, *non-maleficence* refers to privacy, security, and "capability caution," characterized as being intimately linked to individuals' access to, and control over, how personal data is used. Third, *autonomy* means the power to decide (or whether to decide), striking a balance between the decision-making power we retain for ourselves, and that delegated to artificial agents. Fourth, *justice* refers to promoting prosperity and preserving solidarity, seeking to eliminate all types of discrimination. Lastly, *explicability* refers to enabling the other principles through intelligibility (e.g., how does it work?) and accountability (e.g., who is responsible for the way it works?), stressing the need to understand and hold to account the decision-making processes of AI.

Similarly, Jobin et al. (2019) investigated whether a global agreement on ethical AI principles is emerging. Through mapping and analyzing the current corpus of principles and guidelines on ethical AI, the authors found that five principles capture every one of the 47 principles contained in the six high-profile, expert-driven documents they analyzed. Their results reveal a global convergence emerging around five ethical principles—transparency, justice and fairness, non-maleficence, responsibility and accountability, and privacy. The principle of *transparency* comprises efforts to increase explainability, interpretability and other acts of communication and disclosure. The principle of *Justice and fairness* refers to the aspects of justice, fairness, consistency, inclusion, equality, equity, (non-)bias, (non-)discrimination, diversity, plurality, accessibility, reversibility, remedy, redress, challenge, access, and distribution. *Non-maleficence* encompasses general calls for safety and security and states that AI should never cause foreseeable or unintentional harm. In terms of *responsibility and accountability*, specific recommendations include acting with "integrity" and clarifying the attribution of responsibility and legal liability. Finally, *privacy* is often presented in relation to data protection and data security.

The framework proposed by Jobin et al. (2019) shares three principles with those described by Floridi and colleagues (Floridi & Cowls, 2022; Floridi et al., 2018): transparency (explicability), non-maleficence, and justice (and fairness). The privacy principle in Jobin et al.'s (2019) framework is considered a dimension of the non-maleficence proposed by Floridi and colleagues. Therefore, the major differences between the two overarching frameworks are that the principle of responsibility and accountability is included in Jobin et al.'s (2019) framework while the principles of beneficence and autonomy are included in the framework proposed by Floridi and colleagues (Floridi &

Cowls, 2022; Floridi et al., 2018). This study exploring ethical AI in higher education adopts both frameworks of ethical AI principles to inform the data analysis and interpretation.

Based on ethical AI principles (Floridi et al., 2018), previous research has introduced the ethical task–AI fit framework, which emphasizes evaluating the compatibility of tasks with AI technology (Bankins, 2021; Sturm & Peters, 2020). GenAI, a new AI model, has demonstrated its ability to create new content based on the training data. As users increasingly adopt GenAI as a tool in their daily lives, human behavior must be accounted for in the ethical use of technology. Thus, the human-like language and the output generated by GenAI demonstrate the necessity to assess the people–AI fit using the five ethical principles. In the educational context, Deng and Joshi (2024) have argued that ethical consideration of GenAI should incorporate human behavior to assess the people-AI fit and apply the task-AI fit framework to analyze the interactions among the ethical principles, student behavior, and academic outcomes.

Technology affordance theory

The concept of affordances was first introduced by Gibson (1966) to refer primarily to the possibilities of action provided by objects in the environment. Objects are not perceived as what they are but rather as what they can do (Gibson, 1986). Information systems (IS) scholars have used the term to describe the possibilities for action offered to an individual by an object (e.g., Leonardi, 2011; Markus & Silver, 2008). *Affordance* is defined as "the potential for behaviors associated with achieving an immediate concrete outcome and arising from the relationship between an object (e.g., an IT artifact) and a goal-oriented actor or actors" (Volkoff & Strong, 2013, p. 823). The conceptualization of affordances in information systems highlights the action potential of technology. The interaction between one actor and a technology can generate more than one affordance, resulting in multiple outcomes (Treem & Leonardi, 2013; Volkoff & Strong, 2013). Yet the use of IT features or a combination of the features is in the disposition of the actors themselves. Realizing the action potential of technology depends on the goals and abilities of the actors (Faraj & Azad, 2012).

The affordance lens is a powerful tool for helping researchers understand the choices made regarding technology and the outcomes of those choices. Consider social media technology as an example. In higher education, social media use can promote social engagement and mitigate the exclusion experienced by underserved students. Upon analyzing the narratives of 102 FGCSs regarding their experiences of using social networking technologies in college, Gonzalez and Deng (2023) revealed four actualized affordances (interconnection, inspiration, insightfulness, and intense comfort) by three types of social media users (community builders, scholars, and information seekers), shedding light on technology usage for social inclusion outcomes.

Methods

This study adopts a mixed-methods approach involving both qualitative and quantitative analyses to answer the three research questions: qualitative analysis provides insights for RQ1 and RQ2, while quantitative analysis addresses RQ3. Qualitative and quantitative analyses complement each other and potentially provide a richer exploration of the linkages across variables (Mingers, 2001).

Research site

The research took place in a public university in the United States. The university is known as a minority-serving institution, with 69% of students being Hispanic or Latino, 11% Black or African American, and 8% Asian or Pacific Islander. In the United States, minority-serving institutions are institutions of higher education that enroll a high percentage of minority students such as African American, American Indian, Hispanic/Latino, and Pacific Islander (Espinoza, 2024). Most students in this university are underserved students. In 2022, approximately 92% of undergraduate students were considered underserved (meeting at least one of the ethnicity, income, and generation criteria), among which, 30% met all the criteria.

Data collection

The researchers designed a ChatGPT activity flow and created an online survey asking students about their perception of using ChatGPT in learning. The survey consisted of key questions such as “Prior to the class where you received this survey, have you used ChatGPT for any task?” “How do you feel about the following statements on using ChatGPT in college education (1=Strongly Disagree; 5=Strongly Agree)?” “What do you consider the ethical use of ChatGPT in academic study environments?” In the survey, we intentionally did not provide the definition of ethical AI to students because the objective of the study was to elicit students’ viewpoints on the ethical use of GenAI. The survey also included questions on students’ characteristics: age, gender, race or ethnicity, employment status, etc. The survey was approved by the Institutional Review Board (IRB) of the university to ensure ethical research.

The researchers invited instructors in the business college of the research site to encourage their students to participate in the study. Four instructors voluntarily agreed to distribute the survey and related ChatGPT activity to their students during the last two weeks of classes in May, June, July, and December 2023, respectively. Each time we assigned different, non-consecutive, participant ID numbers to the respondents. A total of

186 students from seven classes were invited to participate in the survey. After two reminders in each round of data collection, we received 77 valid responses, representing an overall response rate of 41.4%.

Participant characteristics

Most student participants were non-White: 53% Hispanic/Latino, 19% Black/African American, and 9% Asian/Pacific Islander. Also, 60% were first generation college students (FGCSs) and 79% were employed (57% full-time and 22% part-time). Since the participating classes were higher-level university courses, most students were juniors or above, and four-fifths were aged 22 or older. The participant characteristics are consistent with the student demographics university-wide in terms of ethnicity, Pell-grant eligibility (a proxy for low-income status), employment status, and gender, while having a higher representation of Black students, FGCSs, and senior and graduate students. Among the 77 participants, 23 had prior experience with ChatGPT while 54 did not. Table 1 presents the participant characteristics.

Table 1

Participant characteristics (N = 77)

Characteristics	Frequency	Percent	University data, 2022-23
Ethnicity			
Asian or Pacific Islander	7	9%	8%
Black or African American	15	19%	11%
Hispanic or Latino	41	53%	69%
White/Caucasian	6	8%	6%
Other	2	3%	6%
Prefer not to answer	6	8%	
First Generation Student Status			
FGCS	46	60%	47%
Non-FGCS	25	32%	
Prefer not to answer	6	8%	
Pell Grant Eligibility*			
Eligible	41	53%	58%
Not eligible	25	32%	
Prefer not to answer	11	14%	
Employment			
Employed full-time	44	57%	
Employed part-time	17	22%	
Not employed	16	21%	26%
Gender			
Female	40	52%	62%
Male	33	43%	38%
Prefer not to answer	4	5%	
Class/Year			

Freshman	1	1%	21%
Sophomore	4	5%	10%
Junior	21	27%	25%
Senior	37	48%	34%
Graduate	14	18%	11%
Age			
18-21	14	18%	N/A
22-29	31	40%	N/A
30-39	22	29%	N/A
40-49	7	9%	N/A
50-59	2	3%	N/A
Prefer not to answer	1	1%	
Prior ChatGPT experience			
Yes	23	30%	N/A
No	54	70%	N/A

Note. *Eligible for U.S. Federal Pell Grants targeted at undergraduate students with exceptional financial needs.

Qualitative analysis and findings

Data coding and thematic analysis

Thematic analysis was performed to answer RQ1 and RQ2. Thematic analysis is a qualitative method for identifying, analyzing, and reporting certain themes or patterns across an entire data set (Braun and Clark, 2006; Clarke et al., 2015). Following the guidelines articulated by Braun and Clark (2006), we conducted thematic analysis to interpret student narratives regarding student perceptions of the ethical use of ChatGPT in academic environments ("What do you consider the ethical use of ChatGPT in academic study environments?"). First, we performed an open coding of student narratives to identify first-order codes. Then we sorted and grouped the codes in higher-order themes based on their commonalities and collated each code's data extracts to its corresponding theme. Next, we iteratively refined the codes by screening all collated extracts for each theme and made the necessary revisions of the code label informed by ethical AI principles. Finally, we checked for missing codes and organized the subgroup codes in a hierarchical structure. Table 2 describes the coding scheme, definitions, and examples. Our coding scheme was informed by prior ethical AI research (Floridi & Cowls, 2022; Floridi et al. 2018; Jobin et al., 2019) and by our data.

Table 2

Data coding scheme, definitions and examples

First-order code	Definition	Example
Accountability	Acting with ‘integrity” and clarifying the attribution of responsibility and legal liability (Jobin et al., 2019) and stresses the need to hold to account the decision-making process of AI (e.g., “Who is responsible for the way it (AI) works?”) (Floridi et al. 2018; Floridi & Cowls, 2022)	I think ethical use of ChatGPT is by being transparent and having integrity (P48)
Autonomy	The power to decide (or whether to decide), striking a balance between the decision-making power we retain for ourselves, and that delegated to artificial agents (Floridi et al. 2018; Floridi & Cowls, 2022)	Ethical use of ChatGPT is to use it as a resource for better understanding of lessons or topics that could be more difficult for a student (P59)
Explicability	Enabling the other principles through intelligibility (e.g., how does it (AI) work?) stressing the need to understand the decision-making processes of AI (Floridi et al. 2018; Floridi & Cowls, 2022).	The AI’s outputs (ChatGPT responses) are adequately explainable for the task. ChatGPT can provide examples, teaching and many other information so students can be successful (P64)
User compliance	Users’ compliance with AI use guidelines and policies established in the user environments (Derived from this study)	I do not use ChatGPT unless it's confirmed we can use outside sources (P49)
User transparency	User behavior of self-disclosure, disclosing if or how AI is used in their academic work (Derived from this study)	Letting the reader aware that the system [ChatGPT] was used and it's not someone's own words (P35)

To ensure the reliability of the analysis, the two researchers first performed the coding independently by following the coding scheme before comparing their respective coding results. The inter-coder agreement is 88%, representing a high level of reliability. We finalized the results by resolving the coding discrepancies through extensive discussions and reexamination of the participant responses. For example, in the initial coding of the response, “I do not use ChatGPT unless it's confirmed we can use outside sources,” one researcher coded it as “User self-disclosure” and the other coded it as “Compliance”. After careful deliberation, the two researchers agreed that the response refers to user’s behavior to comply with classroom AI use policies and procedures and eventually refined this code as “User compliance”. During the thematic analysis, we practiced reflexivity, both individually and through team discussion.[1]

Table 3 illustrates our data coding and analysis process from revealing the first-order codes to grouping them into higher-order categories. As shown in the first response, two concepts—explicability and use purpose—were revealed to be associated with ethical AI. Both led to higher-order categories related to affordances in ethical AI, e.g., ethical AI affords value (e.g., a principle) and affords a utility (e.g., use purpose). Similarly, in the second response, the first-order code of user transparency and compliance led to the higher-order category of achieving ethical AI through user behavior in being transparent and compliant.

Table 3

Illustration of data coding and analysis process through examples

Respondent's narrative	Relevant phrases	First-order codes	Higher-order categories	Final themes
Response 1: "With all due respect, ChatGPT can explain material easier than a professor. And even before ChatGPT, most of the students relied on tutoring or the internet to find ways of solving problems or understanding the material. Ethical use of ChatGPT would be using it for further understanding of the material as the machine will keep generating different answers with different approaches." (P49)	"ChatGPT can explain material" "the machine will keep generating different answers with different approaches"	Explicability	Ethical principle: Ethical AI is achieved when technology demonstrates one of its ethical principles, e.g., explicability	Value affordance
	"using it for further understanding of the material"	Purpose of use (resource)	Use purpose: Ethical AI is achieved when technology affords a certain use purpose (e.g., as a tool or resource)	Utility affordance
Response 2: "The ethical use of ChatGPT in academic study means that you are disclosing the use of software or using only in circumstances distinctly allowed to use AI technology for help." (P85)	"disclosing the use of software" "using only in circumstances distinctly allowed to use AI technology for help"	User transparency User compliance	User behavior: Ethical AI is achieved when user behavior demonstrates transparency and compliance	User behavior

Themes on ethical considerations in GenAI use

The qualitative analysis revealed six themes addressing RQ1 on ethical considerations arising in student use of GenAI. The first two themes also addressed RQ2 on GenAI affordances in the academic setting: ethical considerations were concerned not only with the utilities afforded through user interaction with the use of technology (i.e., utility affordances) but also with the values incorporated in the design and enacted in its use (i.e., value affordances). The third and fourth themes reflect user behavior and use outcomes while the fifth and sixth themes capture the considerations of ethical AI use as conditional or non-existent. Table 4 summarizes the six themes that are detailed in this section.

Table 4

Six themes on ethical AI from underserved students' perspective

Theme number and name	Theme description
1-Utility Affordances	Ethical AI is determined by utility affordance by AI: GenAI affords the intended functions of the technology artifact for improving information processing and work productivity.
2-Value Affordances	Ethical AI is determined by value affordance by AI (ethical AI principles): GenAI affords the values of ethical AI principles, e.g., autonomy, explicability, responsibility and accountability.
3-User Behavior	Ethical AI is evaluated from user behavior: Users maintain ethical conduct in their AI usage, such as citing ChatGPT for the AI-generated output, disclosing the use of ChatGPT during the work process, etc.
4-AI Use Outcomes	Ethical AI is evaluated from AI use outcomes: The perceived consequence of using GenAI on user behavior or performance, such as motivating an individual to overcome barriers in a work process and make progress on the work.
5-Contingency of Ethical AI Use	Ethical AI is conditional: The ethical use of GenAI depends on what it is used for and how
6-Pessimistic View of Ethical AI Use	Pessimistic view of ethical AI use: Users perceived that ethical use of GenAI does not exist in the academic setting.

Theme 1. Utility affordances

Students judged ethical AI use based mainly on the affordances of the technology for enhancing their learning in multiple ways: (1) searching for information; (2) brainstorming ideas; (3) structuring content; (4) generating a study guide; (5) improving existing work; (6) personalizing their learning; and (7) interactive learning. We consider these AI affordances "Utility Affordances," as they lead to achieving utility, the perceived advantages of using AI for learning (Long & Magerko, 2020).

Searching for Information. ChatGPT use was considered ethical because it afforded participants' information search. The AI tool was viewed as the equivalent of a search engine or dictionary. Most participants highlighted ChatGPT as a useful study tool for information seeking: "I think that using ChatGPT to learn more on a subject is ethical. An example can be by only using it to gather more information" (P111). In addition, some pointed out its convenience: "Instead of using search engines or dictionary, or even flip old and heavy books, this can be handy" (P118).

Brainstorming Ideas. ChatGPT was found useful for eliciting initial ideas when working on a course assignment. Because of the GenAI affordance for brainstorming, participants considered the AI use ethical. This finding is reflected in two responses: "Ethically the software may be used to assist in formulating research questions or ways to word hypotheses" (P63) and "I think that an example of using ChatGPT ethically is like asking the AI for ideas to go off of" (P125). P125 further provided an example of a course project on developing a bakery business plan: "I could ask ChatGPT 'Give me 10 names for bakeries' and then proceed to use that and put my time into another part of the project."

Structuring Content. Participants reported using the GenAI tool to paraphrase or summarize lengthy texts, thus helping them digest a large volume of information. They considered the GenAI affordance of structuring content ethical. Examples include paraphrasing a quote and summarizing a book or movie to save time when writing reports (P67) and using ChatGPT to help digest information from PDFs and PowerPoints (P120).

Generating a Study Guide. Participants considered it helpful to use ChatGPT to generate a study guide. Benefiting from this affordance, they considered the GenAI use ethical. One participant stated that an ethical way of using ChatGPT was "to ask it to create a potential study guide for an upcoming exam or even create a mock exam" (P104). This perception was elaborated by another participant: "Some classes do not provide study guides for exams, so it could be helpful to use ChatGPT to generate a study guide for additional studying" (P75).

Improving Existing Work. Participants considered it ethical to use the AI tool to improve their existing coursework. They perceived it ethical to use ChatGPT for reviewing and revising coursework they had completed. One participant mentioned that "after researching and drafting a paper a student could utilize ChatGPT to tweak the work" (P45), and another emphasized the purpose of using ChatGPT to improve one's work, not copy the ChatGPT-generated content (P114).

Personalizing Student Learning. Participants often viewed ChatGPT as a personal coach or tutor who provided them with personalized feedback. Such GenAI use was considered ethical. Two participants elaborated on their experiences: one viewed ChatGPT "as a helping hand when learning how to study better or what to study on a subject" (P119) and the other considered ChatGPT "an amazing AI tool that provides information about various topics and provides personalized learning" (P125). A third participant (P126) even used the library as an analogy to explain the personalized guidance provided by ChatGPT in learning a difficult subject and stated that ChatGPT "can be a personal guide when it comes to learning programming, writing, etc. … to learn from [its output] instead as if you were going to the library to study with limitless amount of sources to learn from."

Interactive Learning. Some participants appreciated the interactivity afforded by GenAI in their learning process. They personalized ChatGPT and referred to it as a classmate or best friend. They considered such GenAI use ethical, as their learning benefited from such interactivity. Two quotes demonstrate this finding: "I could possibly use ChatGPT as if it were a classmate and talk to it about possible ways of doing the assignment" (P47) and "Ethical use of ChatGPT would be using it for further understanding of the material, as the machine will keep generating different answers with different approaches. ChatGPT is my best friend!" (P49).

Theme 2. Value affordances

Participants also assessed ethical AI use from the value perspective. Three values were expressed frequently: explicability, accountability, and autonomy.

Explicability. Participants considered their AI use ethical when they believed that ChatGPT delivers the value of explicability in each user-AI interaction. Common phrases include "explain materials easily" and "provide examples that are very detailed for clear understanding."

> I believe ChatGPT can be used ethically in academic study environments when it is used as an aid in the process of arriving at a solution, result, or conclusion for a larger problem, e.g. to clarify areas of confusion, thus enhancing understanding of the subject matter and accelerating the progress of learning and/or the task at hand. (P61)

Accountability. The value of accountability is reflected in the AI use. A few respondents emphasized the need to hold users accountable for their decisions in using AI in the academic setting. This value is reflected in the remark:

> For me using ChatGPT will definitely help the students to get answers from the different tasks that the professor will be giving. Taking into account that plagiarism might be one of the problems in this app. We as students must know how to use our own words and be truthful that every work that we pass is our own and not others' craft. (P87)

Autonomy. The value of autonomy was demonstrated when participants believed they had the power to decide when and how to use the GenAI tool. One participant clarified his purpose for using ChatGPT: "Just like using Google, or Physical books for research purposes - I believe that should be ChatGPT's form of usage" (P76). Another participant elaborated on how and when he/she chose to use ChatGPT: "As a form of research only because when I used it for my project it was easier than to google info" (P86).

Theme 3. User behavior

Ethical use of AI can be assessed from the behavior of those using it. Two types of behavior were revealed: user transparency and compliance. First, when considering ethicality from user behavior, participants frequently mentioned their appropriate *disclosure of AI use, achieving transparency* in their work process. One participant referred to such disclosure as "letting the reader [be] aware that the system [ChatGPT] was used and it's not someone's own words" (P35). This perception was echoed by another participant:

> I think ethical use of ChatGPT is by being transparent and having integrity. If ChatGPT is being used I think it should be noted in a way or referenced at least that the feature was used. (P48)

Second, *compliance* behavior means that users have complied with AI use guidelines and policies established in the user environments. For our study participants, ChatGPT use was ethical if they followed the policies applicable in an academic setting. One participant (P54) explained: "It is not cheating as academic study because they are following to principles of their work goals." Another participant (P88) echoed this idea: "The ethical use of ChatGPT in academic study means that you are using [it] only in circumstances distinctly allowed to use AI technology for help."

Theme 4. AI use outcomes

Some participants made their judgment of ethical AI use based on the perceived outcomes of such use. Our analysis revealed two opposite consequences.

Motivating Student Learning. Some participants believed that ChatGPT use could motivate them to overcome barriers during their learning. As shown below, the participant explained the brainstorming afforded by ChatGPT and the outcome of such use:

> I believe that using ChatGPT as a base or starting point to get you in the right direction is ethical. You may face a question that you have no idea how to attack it but asking ChatGPT may give you a better idea and help you to not procrastinate. (P97)

De-Motivating Student Learning. In contrast, some participants raised the concern that ChatGPT provided the answers to students, who just copied and pasted what they needed from the ChatGPT output. They believed such use is unethical because it prevented a student from engaging in active learning. This concern is reflected below:

> The ethical issue with ChatGPT is it takes the critical thinking and analysis out of assignments. Students will only have to type questions to get what they need and move on. (P77)

Theme 5. Contingency of ethical AI use

Some participants believe that ethical AI use was possible, but it was contingent upon certain situations. While participants found that utilizing ChatGPT was beneficial for their information search, they disapproved of relying entirely on the GenAI tool for completing a class assignment. Copying ChatGPT answers word-for-word was considered unethical. One participant (P102) explained, "I think it becomes unethical when it is used to complete assignments entirely, with no effort to learn the subject." The contingency view is also reflected below:

> I would consider the ethical use of Chat GPT in certain circumstances. I think that using the answer provided word for word is unethical [because] it is not your work. However, using [it] as a form of idea generation is a great way to utilize ChatGPT. (P99)

In some cases, participants articulated contingency factors associated with the background of ChatGPT users. One contingency is the knowledge base of the users. If a user has acquired knowledge about a subject matter or topic, then the user can benefit from the AI tool for the variety of affordances discussed above. One participant (P81) explained that ChatGPT should be used only “when you are very confident in your personal understanding of the material that has been presented by the instructors of the official courses.”

Another contingency is that when students encounter a barrier in their learning activities, using ChatGPT to enable them to continue learning was considered ethical. As one participant (P90) elaborated, an ethical use of ChatGPT would be “using this software when you are stuck, [and] can't access the textbook/or the professor when you have a question.”

Theme 6. Pessimistic view of ethical AI use

A small portion of participants (n=8 or 10.4% of the sample) did not believe that any usage of the AI tool in academic environments was ethical. They held the pessimistic view because they perceived that using GenAI in education would have a detrimental effect on their education, including the development of critical thinking capability. This sentiment is reflected in two remarks:

> I don't think it [ChatGPT] has any place in an academic environment. Unless your field is the study of AI, leave it out. It takes all of the critical thinking away from education. (P69)

> ChatGPT should be seen as a form of plagiarism, by completely utilizing this program, I don't think students will build important educational skills. For example, advanced writing. (P76)

Quantitative analysis and results

We performed quantitative analyses using Mann-Whitney *U*-tests and ordinal logistic regressions to answer RQ3: whether students’ perceptions of the ethical use of GenAI vary by their demographic and socioeconomic background. The Mann-Whitney *U*-test is a nonparametric test often used to determine the statistical significance of differences between two independent groups (Conover, 1999). It does not assume a normal distribution of the data (an assumption required for parametric tests such as the independent samples *t*-tests). Instead of comparing the sample means, the Mann-Whitney *U*-test compares the ranks of values from two independent groups, making it particularly useful when dealing with ordinal data or when the sample size is small (Nachar, 2008). The research hypothesis states that the ranks of one group are systematically higher or lower than those of the other and the *U* statistic is calculated based on the sum of the ranks and the sample size of each group (Corder & Foreman, 2014). Beyond simple group comparisons by the Mann-Whitney tests, we performed ordinal logistic regressions to predict the ordinal dependent variable given a set of independent variables (Agresti, 1996).

Student perceptions of using ChatGPT in education

After two ChatGPT practices led by their instructors, students were asked to rate their agreement with the following statements on a 5-point Likert scale (1=Strongly Disagree; 5=Strongly Agree): (1) Using ChatGPT to assist my schoolwork will negatively affect my skill development; (2) Using ChatGPT to complete class assignments is cheating; (3) Using ChatGPT to complete exams and quizzes is cheating; (4) It is possible to use ChatGPT in an ethical way to help complete my class assignments; (5) It is possible to use ChatGPT in an ethical way to help complete my class exams and quizzes; and (6) Using ChatGPT to assist my schoolwork will motivate me to continue learning.

Student responses to these statements demonstrate that their opinions diverged on whether it is ethical or beneficial to use ChatGPT in education, as shown in Table 5. If we consider those participants who agree or strongly agree with a statement as one group, we find that 33% of the participants perceived the negative effect of ChatGPT use on their skill development (Statement 1) while 42% of the participants considered the benefit of ChatGPT use in motivating them to continue learning (Statement 6). Moreover, 43% of the participants considered using ChatGPT to complete class assignments as cheating (Statement 2), but more participants (65%) perceived the use of ChatGPT to complete exams and quizzes as cheating (Statement 3). Interestingly, 78% of the participants agree or strongly agree that it is possible to use ChatGPT in an ethical way to help complete class assignment (Statement 4), but only 46% think so for exams and quizzes (Statement 5).

Table 5

Student agreements to using ChatGPT in higher education

Statement	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
#1	8%	32%	28%	21%	12%
#2	7%	30%	20%	26%	17%
#3	5%	12%	18%	29%	36%
#4	4%	1%	17%	37%	41%
#5	11%	22%	21%	26%	20%
#6	8%	11%	39%	24%	18%

Moreover, student ratings on these 5-point Likert-scale statements are consistent with their narrative responses to the open-ended question analyzed in the previous section. For example, among the eight students who expressed a pessimistic view of the ethicality of AI use, the median values of their responses to the six statements are 4, 4.5, 4.5, 3, 2, and

2.5 points, respectively. That is, these students tend to give higher ratings (Agree or Strongly Agree) to the negative statements (Statements 1-3) and lower ratings (Disagree or Neutral) to the positive statements (Statements 4-6).

In general, students seemed to be more willing to use ChatGPT in assignments than in exams and quizzes, but many worried that ChatGPT might hinder their skill development or discourage their own learning. Next, Mann-Whitney *U*- tests were performed to examine whether student perceptions of the ethical use of GenAI varied by their demographic and socioeconomic status.

Comparisons of student perceptions by individual background

We first conducted Mann-Whitney *U*-tests to compare student perceptions of the ethical use of ChatGPT between different groups of students. Using the 0.05 significance level, the tests show three statistically significant results: (1) compared to non-FGCSs, FGCSs have a higher level of agreement with Statement 2 "Using ChatGPT to complete class assignments is cheating" ($U = 392.5$, $z = -2.266$, $N_0 = 25$, $N_1 = 46$, $p = .023$, mean rank for $N_0 = 28.70$, mean rank for $N_1 = 39.97$); (2) FGCSs have a lower level of agreement with Statement 6 "Using ChatGPT to assist my schoolwork will motivate me to continue learning" ($U = 393$, $z = -2.285$, $N_0 = 25$, $N_1 = 46$, $p = .022$, mean rank for $N_0 = 43.28$, mean rank for $N_1 = 32.04$); and (3) compared to their counterparts, Pell-eligible (low-income) students have a lower level of agreement with Statement 5 "It is possible to use ChatGPT in an ethical way to help complete my class exams and quizzes" ($U = 324$, $z = -2.553$, $N_0 = 25$, $N_1 = 46$, $p = .011$, mean rank for $N_0 = 41.04$, mean rank for $N_1 = 28.90$). The Mann-Whitney *U*-test results are reported in Tables A.1 and A.2 of the Appendix.

Similar tests were also performed on gender, race, and ethnicity, but the differences between male and female students, between Hispanic and non-Hispanic students, and between Black and non-Black students were not statistically significant (results not reported here). In sum, the Mann-Whitney *U*-tests revealed a statistically significant difference between FGCSs' and non-FGCSs' perceptions of ethical GenAI use, as well as between Pell-eligible students and their counterparts. Next, we employ regression techniques to predict the effects of FGCS status and Pell eligibility on students' perceptions of the ethical use of ChatGPT in education.

Effects of FGCS status and Pell eligibility on student perceptions

Ordinal logistic regression analyses were conducted to investigate the relationship between the dependent variable—student perception of the ethical use of ChatGPT in education (an ordinal variable)—and the independent variable—FGCS status (yes=1; no=0) or Pell eligibility (yes=1; no=0)—controlling for students' prior ChatGPT experience (yes=1; no=0). Because of the small sample size, the three binary predictors could not all be included simultaneously in a single model. Including all predictors would have produced substantial data sparsity, with more than 30% of outcome-by-predictor cells containing zero observations, which can compromise the stability and reliability of parameter estimates in ordinal logistic regressions. Accordingly, separate models for different statements were estimated, each including one focal independent variable (FGCS or Pell eligibility) and prior ChatGPT experience as a control. No interaction terms were included in the analyses.

Table 6 reports the regression results. Model 1 indicates that FGCSs are more concerned than non-FGCSs that using ChatGPT to complete class assignments is cheating (Statement 2), all else being equal. Model 2 shows that compared to their counterparts, Pell-eligible (low-income) students are less confident about the possibility of using ChatGPT in an ethical way to help complete class exams and quizzes (Statement 5), all else being equal. Model 3 suggests that, all else being equal, FGCSs are more skeptical than non-FGCSs that "Using ChatGPT to assist my schoolwork will motivate me to continue learning" (Statement 6), and that students with prior ChatGPT experience are more optimistic about its motivating benefits than students who had not used ChatGPT before. Similar regressions were also performed on other statements (Statements 1, 3, and 4), but none of the independent and control variables showed statistical significance (results not reported here).

Table 6

Regression results

Variables	Model 1 Statement 2	Model 2 Statement 5	Model 3 Statement 6
FGCS	1.063**		-1.212**
	(0.465)		(0.476)
Pell-eligible		-1.342***	
		(0.489)	
Prior ChatGPT	-0.451	0.547	1.055**
	(0.468)	(0.503)	(0.486)
Observations	71	66	71
Pseudo R-Square	0.082	0.114	0.129

Note. All models are ordinal logistic regressions. Coefficients (log odds) are reported. Standard errors are in parentheses. ** $p<0.05$. *** $p<0.01$.

In summary, the results of the ordinal logistic regression analyses indicate that FGCS status and Pell eligibility are significant predictors of students' perceptions of the ethical use of ChatGPT in education. Specifically, FGCSs and Pell-eligible (low-income) students are more skeptical about using ChatGPT in education than their counterparts. In contrast, students with prior ChatGPT experience have more positive views of using ChatGPT to motivate their learning than students without such experience. The results of the ordinal logistic regression analyses are consistent with those of the Mann-Whitney *U*-tests and have the advantage of controlling for the effect of prior ChatGPT experience.

Discussion

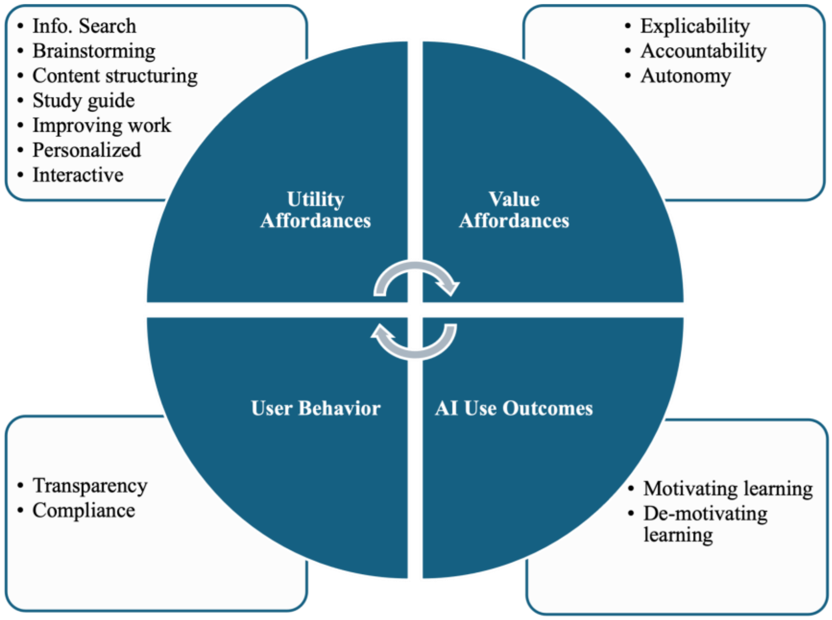
This mixed-methods study aims to understand underserved students' use of GenAI by integrating ethical considerations and the technology affordance lens. The qualitative analysis, which addressed RQ1 and RQ2, revealed that ethical considerations in GenAI use depended on user perspectives: some users shared their perspectives on the affordances of GenAI (utility or value affordances), while other users associated ethical AI use with their user behavior (e.g., how to use GenAI) or the consequences of such technology use. Furthermore, the quantitative analysis, which addressed RQ3, demonstrated that FGCSs and low-income students were more skeptical about using ChatGPT in education than their counterparts, while prior ChatGPT experience helped in developing a positive view of using the tool to motivate learning.

An integrated model of ethical considerations in GenAI use

The analysis revealed the multifaceted nature of ethical considerations in GenAI use, which concerned user perceptions of the technology affordances and design value, user reflections on their use behavior and the consequences, and the contingency factors. Our analysis of perceived ethical GenAI use by underserved students suggests that GenAI use for education was considered ethical when at least one of the ethical use dimensions was present. Thus, based on the findings, we propose an integrated model of ethical considerations in GenAI use. The model consists of four major components as depicted in Figure 1. Our study has provided evidence that ethical considerations in GenAI use are not only related to user behavior and use outcomes but also associated with various types of GenAI affordances. This updated view of ethical consideration goes beyond the view of computer abuse in organizations (Lowry et al., 2014; Mingers & Walsham, 2010).

Figure 1

An integrated model of ethical considerations in GenAI use



GenAI use raises awareness of new digital divide

This study focused on underserved students' perception of the ethical use of GenAI in a minority-serving public university, but the survey also included an open-ended question on their opinions of and experiences with the impact of AI on their education and future work. Analysis of their narratives revealed their concerns that AI may be widening the digital divide that this underserved student population is struggling with. A Hispanic student raised the question, "If a student does not have access to a computer with Wi-Fi, how are they even going to use ChatGPT?" Similarly, another student (Junior, male, Asian) elaborated on the worrisome impact of AI on the underserved communities and their future:

> I believe AI will affect the digital divide as it may create more problems for these struggling communities. As universities allow students and professors to use ChatGPT and the capabilities of AI, students will fall behind as the digital divide already sets them back. To illustrate, those who lack the proper technology, Wi-Fi and computers, those students will further lack the accessibility to ChatGPT.

As participants in our study are mostly underserved students (e.g., 60% were FGCS and 79% were employed), providing them with sufficient technological resources (e.g., computers, Internet access) has become critical for them to realize the affordances of GenAI and to reduce the risk of being left farther behind in the age of AI. This call-for-action is consistent with recent research finding that individuals with low socioeconomic status are associated with lower digital confidence in understanding and using digital technologies such as AI (Bentley et al., 2024) and that the most vulnerable groups, those with the lowest levels of AI knowledge and AI skills, were mostly older, with lower levels of education and privacy protection skills, than the average users (Wang et al., 2025).

Theoretical contributions

This study applies the technology affordance theory to the novel context of GenAI and empirically identifies specific new affordances: “utility affordances” and the novel "value affordances." The affordance lens has helped information systems researchers understand the choices made about technology and the outcomes of those choices (Leidner et al., 2018). GenAI can trigger individuals to discover the aspects of the technology that provide an opportunity for action. Our study participants described ChatGPT as a useful tool for “information search,” “brainstorming,” and “enhancing their work.” Moreover, they highlighted that ChatGPT afforded personalized and interactive learning, referring to ChatGPT as a study tutor, coach, or even best friend. These results are consistent with prior studies that suggest that the relationship between a user and a technology can lead to not only one but multiple affordances, which can thus result in multiple outcomes (Treem & Leonardi, 2013; Volkoff & Strong, 2013). In addition, our study revealed three values perceived by GenAI users (the underserved students)—accountability, autonomy, and explicability—suggesting a novel type of affordance, “value affordance.”

In our study, participants viewed ChatGPT largely as a tool for their information searches and processing, and their use of this tool has brought not only positive outcomes such as enhanced learning through instant feedback and detailed explanations but also negative consequences such as over reliance on GenAI and the erosion of critical skills. Because of these complex interactions, we consider user behavior, affordances, and outcomes separately when studying ethical AI in the higher education context.

Furthermore, the study findings provide nuances related to the emerging digital divide in the age of AI. Prior studies have suggested both beneficial and detrimental effects of GenAI use on student learning (e.g., Nguyen et al., 2024; Zhai et al., 2024), potentially narrowing or widening disparities between the digital competence of underserved students and their peers. Our study adopted the perspective of underserved students and revealed the benefits of personalized and interactive learning afforded by GenAI and the ethical principles of accountability, autonomy, and explicability demonstrated in their GenAI use. Meanwhile, some study participants articulated the urgency of closing the existing divide (e.g., having access to computers and Wi-Fi) to take advantage of the affordances of AI. How AI technology will affect its users (organizations or individuals) will depend on how its technical capabilities are utilized to achieve its users’ goals.

Practical implications

The study has implications for guiding and promoting effective use of GenAI by students. First, given the importance of utility affordances in ethical GenAI use and the positive impact of prior ChatGPT experience, universities may develop and implement GenAI literacy workshops to help students understand the useful features and potential drawbacks of the new technology. These workshops should not only train students to create effective prompts for various learning purposes (such as writing, summarizing, and brainstorming), but also teach them how to fact-check GenAI-generated responses using critical thinking skills and how to identify potential biases, hallucinations, and outdated information. As Kong and Yang (2025) discovered, a well-structured AI literacy program starting with a conceptual introduction to general machine learning followed by deep learning can significantly enhance AI empowerment among secondary school and university students in terms of impact, creative self-efficacy in AI, and meaningfulness.

Second, a concerted effort by instructors and students to apply the ethical people-AI fit framework would help students clarify the boundaries between ethical and unethical use of GenAI. Course design should incorporate clear AI use guidelines for students to follow, and students need to be reminded of their learning goals and skill development to maintain a balance between using GenAI for improving information processing and relying on GenAI entirely to replace their learning activities. Through ongoing dialogue, collaborative policy-making, and practical case studies, such joint engagement can foster a shared understanding of academic integrity, appropriate tool usage, and the broader implications of AI-assisted work in educational contexts.

Finally, the study revealed the personalized and interactive learning offered by GenAI, which may be especially beneficial for underserved students who encounter barriers to accessing educational resources. By providing writing assistance, tailored feedback, and adaptation to individual learning needs, GenAI helps bridge learning gaps for students with limited access to tutoring, mentorship, and academic tools. As such, educating students, particularly underserved students such as FGCSs with no prior ChatGPT experience on how to effectively use GenAI, has the potential to promote a more equitable and inclusive educational landscape.

Conclusion

This study examined the ethical considerations arising in the use of ChatGPT perceived by underserved university students and revealed the affordances of ChatGPT use for their learning. The qualitative analysis found that ethical considerations in GenAI use depended on user perspectives: some users shared their perspectives on the affordances of GenAI (utility or value affordances), while other users associated ethical AI use with their user behavior (e.g., being transparent and compliant) or the consequences of the technology use.

Furthermore, the quantitative analysis results indicate that underserved students' perceptions of the ethical use of GenAI varied by their demographic and socioeconomic background. Specifically, FGCSs and Pell-eligible (low-income) students were more skeptical about using ChatGPT in education than their counterparts, while students with prior ChatGPT experience had a more positive view of using ChatGPT to motivate their learning than students without such experience. Finally, our proposed integrated model of ethical GenAI use covers not only affordances and ethics principles but also user behavior and perceived outcomes, offering a research model for future large-scale empirical investigations across different GenAI use contexts.

The study has its limitations. First, the sample is from one type of higher education institution. Thus, the findings might not be generalizable in other settings. Second, the potential interactive effects of FGCS status and Pell eligibility were not examined in the regression models due to data sparsity. Lastly, the participants were underserved students from a minority-serving university, so their interpretation of ethical AI is student-centered, focusing on AI use for their academic work. They did not look beyond their user context (e.g., the educational environment) when they considered the ethical issues of AI.

Future research is needed to explore the socio-technical process in the adoption of AI by underserved communities and in other use contexts beyond educational environments. For example, how can we enhance the AI affordances (both utility and value affordances) for underserved populations? How do the features of GenAI shape the utility values it affords? What are the dynamics between large-scale ethical issues in AI development (e.g., biases in training data and algorithms) and those that arise in AI use contexts? Addressing ethical concerns in AI use and development requires concerted efforts from multiple stakeholders and communities. We hope this study provides a starting point to encourage scholars across disciplines to conduct further studies in this emerging research space.

Appendix

Table A.1

Students' perceptions of using ChatGPT in education by FGCS status

Statement	FGCS	N	Mean rank	Sum of ranks	U	Z	*p*
#1	No	25	31.28	782.00			
	Yes	46	38.57	1,774.00	457.000	-1.468	0.142
#2	No	25	28.70	717.50			
	Yes	46	39.97	1,838.50	392.500	-2.266	0.023**
#3	No	25	30.34	758.50			
	Yes	46	39.08	1,797.50	433.500	-1.778	0.075
#4	No	25	32.22	805.50			
	Yes	46	38.05	1,750.50	480.500	-1.214	0.225
#5	No	25	39.02	975.50			
	Yes	46	34.36	1,580.50	499.500	-0.931	0.352
#6	No	25	43.28	1,082.00			
	Yes	46	32.04	1,474.00	393.000	-2.285	0.022**

Note: Mann-Whitney *U*-test. The mean rank is the sum of ranks divided by the group's sample size (N). A significantly different mean rank means one group tends to have higher (or lower) ranks than the other. Total N=71; ** p<0.05.

Table A.2

Students' perceptions of using ChatGPT in education by Pell eligibility

Statement	Pell-eligible	N	Mean rank	Sum of ranks	U	Z	*p*
#1	No	25	34.60	865.00			
	Yes	41	32.83	1,346.00	485.00	-0.375	0.708
#2	No	25	32.84	821.00			
	Yes	41	33.90	1,390.00	496.00	-0.225	0.822
#3	No	25	31.70	792.50			
	Yes	41	34.60	1,418.50	467.50	-0.621	0.534
#4	No	25	34.94	873.50			
	Yes	41	32.62	1,337.50	476.50	-0.511	0.609
#5	No	25	41.04	1,026.00			
	Yes	41	28.90	1,185.00	324.00	-2.553	0.011**
#6	No	25	34.24	856.00			
	Yes	41	33.05	1,355.00	494.00	-0.254	0.799

Note: Mann-Whitney *U*-test. The mean rank is the sum of ranks divided by the group's sample size (N). A significantly different mean rank means one group tends to have higher (or lower) ranks than the other. Total N=66; ** p<0.05.

Abbreviations
FGCS: First generation college student; GenAI: Generative artificial intelligence; ICT: Information and communication technologies; IRB: Institutional Review Board; IS: Information systems; LLM: Large language model; RQ: Research question.

Endnotes
[1] In this study, we identified themes at the interpretive level to reveal the underlying ideas and assumptions within the data (Braun & Clarke, 2006). As the researchers of the study, we have actively and critically examined our own assumptions and biases, recognizing that themes are a product of our engagement with the data. We understand that our experiences working with underserved student populations might have influenced our analytical lenses. We practiced reflexivity during the thematic analysis individually and through team discussions by asking ourselves, “Are we making assumptions about a participant’s words?” Our two-person research team first read all study participants’ responses individually to build an overall sense of the data before coding a sub-sample of 25 responses individually. We then came together to discuss and debate our understanding of the data set as we compared our coding results and resolved discrepancies in the data coding and analysis.

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Author’s contributions
The authors contributed equally to the research design, conceptualization, data collection, data analysis, interpretation of results, and manuscript writing.

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Availability of data and materials
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Declarations

Competing interests
The authors declare no known competing interests.

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