



The social costs of AI: the influence of GenAI interaction on social undermining behavior among college students

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Abstract

While generally described as improving learning outcomes, this study explores the potential of GenAI to foster unfavorable social behaviors. Drawing on social cognitive theory, we theorize that frequent interaction with GenAI may lead students to develop objectification as a learned cognitive pattern, which in turn increases the likelihood of engaging in social undermining behavior. We further explored AI cognitive readiness as a moderator, proposing that students with lower AI cognitive readiness are more susceptible to social undermining behavior. Using data from a three-wave survey of 315 Chinese college students whose ages ranged from 18 to 27 years ($M=22.356$, $SD=2.896$), our results indicate that GenAI interaction frequency is positively associated with social undermining behavior, with objectification of others mediating this relationship. Moreover, the indirect effect is stronger for students with lower AI readiness. Our findings highlight the unintended social consequences of GenAI among university students and offer insights for educators on how to integrate GenAI in ways that mitigate negative behaviors. Theoretical and practical implications, including interventions to enhance AI cognitive readiness and reduce objectification through ethical education and collaborative learning, are discussed.

Keywords Interaction with generative AI · Social undermining behavior · Objectification of others · AI cognitive readiness

Introduction

The real problem is not whether machines think but whether men do.

— B.F. Skinner.

The launch of ChatGPT by OpenAI in November 2022 represented a major advancement in artificial intelligence. Within months, its generative capabilities captured a global attention, positioning generative AI (GenAI) tools like GPT-4 as indispensable in education, content creation, and scientific research (Crompton & Burke, 2023; Abdelwahab

et al., 2022; Epstein et al., 2023; van Dis et al., 2023). In education, Gen AI is credited with facilitating personalized learning, improving access to high-quality information, and assisting with complex tasks (Chan & Hu, 2023; Kasneci et al., 2023). Research has largely emphasized its academic benefits, such as enhanced learning outcomes, self-efficacy, and creativity (Essel et al., 2024; Lee et al., 2022; Shahzad et al., 2024; Lee & Chung, 2024; Wong & Looi, 2024). However, beyond its academic utility, emerging evidence suggests that GenAI may potentially reshaping cognition and social behaviors in ways yet to be fully understood (e.g., Gratch & Fast, 2022; Tang et al., 2023; Rasouli et al., 2024; Hou et al. 2025b; He et al. 2023; Zhang et al. 2025). This concern is particularly relevant for college students, a demographic that frequently engages with AI in academic settings, often relying on GenAI for writing assistance and problem solving (Abbas et al. 2024; Crawford et al. 2024; Hou et al. 2025a).

While GenAI is traditionally perceived as a tool, it exhibits its quasi-agent characteristics, such as autonomous learning and human-like interaction (Al Lily et al., 2023; Gray et al., 2025; Rasouli et al., 2024). Individuals often perceive

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AI as a “social agent”, applying human-like expectations to these interactions, which may reshape cognition and interpersonal dynamics (Epley et al., 2007; Tang et al., 2023; Xie et al., 2023; Yang, 2025). Research has linked AI interaction to increased feeling of loneliness, prompting compensatory helping behaviors at workplace as individuals seek alternative forms of social connection (Tang et al., 2023). This aligns with the idea that GenAI can blur the boundaries between technology and human relationships, influencing how individuals perceive and engage with AI-driven agents (Al Lily et al., 2023; Gray et al., 2025). Research on AI chatbots further demonstrate that users may develop relational bonds with AI, treating them as emotional support providers rather than mere functional tools (Xie et al., 2023). These findings suggest that frequent interactions with GenAI may affect how they interpret human-human interactions. Zhang et al. (2025) show that unfair treatment by AI can reduce prosocial behavior in subsequent human interactions (i.e., AI-induced indifference). Their findings illustrate the spill-over effect of human-AI interactions and suggest that unfair AI interactions may desensitize people to the bad behavior of others, reducing their prosociality.

Despite growing interest in AI’s broader social consequences, most research remains focused on perceptions and attitudes toward AI (e.g., Cadario et al., 2021; De Freitas et al., 2023) and its instrumental benefits (Kim & Cho, 2023; Crawford et al., 2024). A critical gap remains in understanding whether and how frequent interactions with GenAI influence subsequent interpersonal behaviors, particularly in academic contexts. Given that students use GenAI predominantly for academic tasks, these efficiency-driven interactions may cultivate a depersonalized, outcome-oriented perspective (Dennis et al., 2023). In highly competitive educational settings, this instrumental mindset may spill over into human-human interactions (Zhang et al., 2025; Yang et al., 2025), increasing social undermining behaviors, which involve intentional actions aimed at hindering others’ social status (Duffy et al., 2002).

Building on these insights, this study investigates the social consequences of interacting with GenAI. Specifically, how such interactions may shape students’ interpersonal cognition and behavior in academic settings. To explore this, we draw on Social Cognitive Theory (Bandura, 1986), which posits that individuals acquire and transfer cognitive patterns through repeated interactions with their environment. In this context, frequent engagement with GenAI’s task-oriented exchanges may lead students to develop objectification tendencies, perceiving both AI and human peers as mere tools or objects rather than autonomous human beings (Fredrickson & Roberts, 1997; Gruenfeld et al., 2008). Once developed, this depersonalized mindset may spillover into human interactions in competitive academic

environments, promoting social undermining—intentional acts aimed at diminishing others’ social status (Duffy et al., 2002). Further, in line with SCT’s focus on cognitive factors influencing behavior, we introduce AI cognitive readiness (i.e., preparedness to understand and interact with AI; Wang et al., 2023) as a moderating variable. We propose that students with greater understanding of AI’s mechanisms and limitations may be less prone to objectifying others, mitigating social undermining behavior.

This study makes several contributions. First, it challenges the prevailing assumption that GenAI’s role in education is purely beneficial (Jensen et al., 2025) by exploring its agent-like role (Al Lily et al., 2023; Gray et al., 2025) and its potential to trigger negative social behaviors among college students. Second, it extends SCT by framing objectification tendency as a learned outcome from GenAI interactions, providing a novel theoretical lens to understand how GenAI usage affects students’ social behavior. This builds on existing research exploring AI’s impact on social relationships (Hohenstein et al., 2023; Darvishi et al., 2024; Zhang et al., 2025). Third, by emphasizing AI cognitive readiness as a buffer, it offers actionable insights for responsible educational integration. Finally, this study contributes to the emerging field of AI-human interaction by elucidating cognitive mechanisms linking GenAI use to social dynamics, advancing beyond the tool-centric focus of prior work (Kim & Cho, 2023; Krügel et al., 2023; Zhang et al., 2025), and considering its broader cognitive and social implications.

Hypothesis development

Interaction with GenAI and social undermining behavior

Social Cognitive Theory (SCT) suggests that individuals acquire behaviors through observation and repeated interaction with their environment (Bandura, 1986). When college students engage with Generative AI (GenAI), they interact with systems that prioritize task completion and efficiency over emotional connection. GenAI’s ability to simulate human-like conversations without genuine emotional depth may lead students to develop impersonal behavior patterns, which could extend into their interactions with others. This process is further reinforced by the Eliza effect, where individuals project human qualities onto AI systems, mistakenly perceiving them as a social agent (Epley et al., 2007). These repeated task-driven, interactions may not only alter students’ perception of AI but also influence their real-world social behavior (Hohenstein et al., 2023).

Moreover, students who regularly interact with GenAI may experience power asymmetry during these exchanges, as students adopt a commanding role, issuing instructions that the AI must follow (Ribino, 2023). This repeated reinforcement of control may cultivate a sense of dominance, potentially reducing sensitivity to others' emotions in subsequent interactions. Zhang et al. (2025) provide empirical support for this spillover effect, demonstrating that individuals who experience unfair treatment by AI may be desensitized and exhibit reduced prosocial behavior toward other humans. Extending this to power asymmetry in AI interactions, frequent engagement with AI in a directive capacity may further desensitize individuals to interpersonal social norms, increasing the likelihood of negative behaviors in human-human interactions (Harrell & Traeger, 2025). Over time, such patterns may increase the likelihood of social undermining behavior—deliberate actions intended to harm or disrupt others in social settings (Dubois et al., 2015; Yu & Zellmer-Bruhn, 2018). College students may be more vulnerable as their cognitive and emotional regulation is still developing, making them more susceptible to transferring learned behaviors from AI interactions to real-world social context (Runions & Bak, 2015). Research also suggests that interactions with AI can lower anticipatory guilt, thus encouraging unethical behaviors (Kim et al., 2023).

Therefore, drawing from SCT and existing research on human-technology interactions, we propose the following hypothesis:

Hypothesis 1: GenAI interaction frequency is positively correlated with higher levels of social undermining behavior among college students.

The mediating role of objectification of others

Building on SCT, which emphasizes the transfer of learned behaviors and cognitions from one context to other social environments, frequent interactions with GenAI may foster objectification of others—a cognitive process where individuals begin to perceive others as less human and more as objects or tools (Andrighetto et al., 2017). In task-oriented environments like those created by AI, individuals may focus on others' functional aspects, leading to a utilitarian view of human interaction (Heflick & Goldenberg, 2009). This phenomenon has been shown to reduce empathy and emotional engagement (Cikara et al., 2010), as interactions mediated by AI often lack the social cues necessary to foster empathy (Mou & Xu, 2017).

Furthermore, objectification has been linked to dehumanization, which fosters aggression and social disconnection (Loughnan et al., 2010, 2017). Similarly, frequent interaction with GenAI for learning and task completion

may subtly reinforce these objectifying tendencies, particularly as they continuously rely on the AI to meet academic or social needs (Hou et al., 2024). By prioritizing task efficiency over emotional engagement, students may begin to view both AI and human counterparts through a utilitarian lens. The Social Interaction Model of Objectification (Gervais et al., 2020) explains this by demonstrating how goal-oriented behaviors—focused on utility rather than human qualities—can lead to dehumanization. As individuals become accustomed to interactions driven by task fulfillment, they are more likely to perceive others as tools for achieving objectives, further entrenching dehumanizing tendencies in their real-life social interactions.

In this context, objectification of others can act as a cognitive mediator that explains how GenAI interactions result in negative social behaviors. Specifically, when students view others through an objectifying lens, they are less likely to experience emotional resonance (Zurbriggen, 2013) and more inclined to engage in social undermining behaviors (Calogero et al., 2021). Thus, this cognitive shift triggered by AI interactions, can transfer to social contexts and shape students' behavior. Therefore, we propose the following hypothesis:

Hypothesis 2: The objectification of others mediates the relationship between the GenAI interaction frequency and social undermining behavior among college students.

The moderating role of AI cognitive readiness

Social cognitive theory emphasizes the role of cognitive factors in determining how individuals process and respond to their environment. These learned behaviors and cognitive processes are often transferred across contexts (Bandura, 1986). In the context of AI interactions, cognitive factors such as AI cognitive readiness become critical in shaping these responses. AI cognitive readiness refers to an individuals' preparedness to understand and interact with AI, including their knowledge of AI's operating principles, awareness of its limitations, and comprehension of its role in human interaction (Wang et al., 2023). Without this readiness, individuals may struggle to regulate their behaviors or expectations during AI interactions, which could extend into their real-life interactions.

Previous studies show that individuals with high AI cognitive readiness are better able to use AI tools effectively while recognizing their limitations. For instance, educators with high AI readiness tend to view AI as a tool for innovation, leading to improved experiences and outcomes in educational settings. Conversely, those with low AI cognitive readiness may perceive AI as a threat, which can result

in avoidance behaviors (Chounta et al., 2022; Luckin et al., 2022).

For college students, high AI cognitive readiness enables them to recognize the functional, non-emotional nature of GenAI, reducing the likelihood of over-relying on it or projecting emotions onto AI (George et al., 2023). This understanding decreases the risk of treating GenAI as a substitute for real human interaction, thereby lowering the tendency to objectify others. In contrast, low AI cognitive readiness can result in misconceptions about AI, leading students to overly depend on GenAI for fulfilling social and emotional needs (Tang et al., 2023; Einola & Khoreva, 2023). In such cases, they may be more likely to treat GenAI as a substitute for human interaction, fostering objectification tendencies in their relationships. This is especially true in non-reciprocal interactions, as frequent AI use can blur the boundaries between virtual and real-life relationships (Morris et al., 2018). Therefore, we propose:

Hypothesis 3: AI cognitive readiness moderates the positive relationship between GenAI interaction frequency and objectification of others such that the positive relationship is weaker when college students have high AI cognitive readiness rather than low.

According to Social Cognitive Theory, cognitive factors such as self-regulation, awareness, influence how learned behaviors are applied to different social contexts (Bandura, 1986). Although SCT does not explicitly reference “cognitive readiness,” the concept aligns with the theory’s focus on cognitive control in regulating behavior. In the context of GenAI interactions, AI cognitive readiness can provide individuals with the tools to critically evaluate and filter learned cognitions from GenAI interactions, such as objectification. Thus, high cognitive readiness can act as a buffer, reducing the likelihood that objectifying tendencies will manifest in negative social behaviors like social undermining (Duffy et al., 2002). Conversely, students with low AI cognitive readiness may find it hard to differentiate between AI-based interactions and real-life social dynamics. This could increase the risk that learned objectifying tendencies from GenAI interactions will transfer into real-world contexts, leading to negative social outcomes (Gratch & Fast, 2022). Therefore, AI cognitive readiness can moderate the indirect relationship between GenAI interaction frequency and social undermining behavior via the mediating role of objectification. Students with high AI cognitive readiness are less likely to engage in social undermining because they can critically assess and limit the impact of learned objectification, while those with low readiness are more vulnerable to transferring these learned behaviors to real-life interactions.

Hypothesis 4: AI cognitive readiness moderates the indirect effect of on social undermining behavior via objectification of others such that the indirect effect is weaker when college students have high AI cognitive readiness rather than low.

The theoretical model of this study is shown in Fig. 1.

Methods

Participants and procedures

Although the use of GenAI among student populations has become increasingly common, some institutions have still implemented restrictive measures to prevent its misuse. To test our research hypothesis, we selected a comprehensive university in Southern China that had not yet issued prohibitions or restrictions on the use of GenAI. This allowed us to recruit participants who freely used GenAI without institutional barriers.

We recruited participants using authors’ social network connections, leveraging platforms such as WeChat official accounts and QQ groups to reach college students with experience using GenAI. These platforms were selected due to their widespread adoption among Chinese college students. Participants were recruited based on the following eligibility criteria: (1) current undergraduate students; (2) self-reported active use of GenAI tools for academic tasks in the past month; (3) geographically limited to students at a large university in Nanchang to control institutional policy variations.

Before data collection, electronic informed consent was obtained from all participants. The consent form outlined the study’s purpose, voluntary participation rights, data anonymization, and secure storage protocols. Data collection was conducted via Credamo (a well-established Chinese online survey platform similar to MTurk or Prolific), which with built-in anti-fraud mechanisms (e.g., response time monitoring) and has been reported to be reliable and feasible by previous studies.

Following Podsakoff et al. (2003), we adopted a three-wave survey design. Unlike cross-sectional designs, which capture data at a single point, this approach provides insights into temporal sequences and minimizes common method bias by collecting data across multiple time points. Data

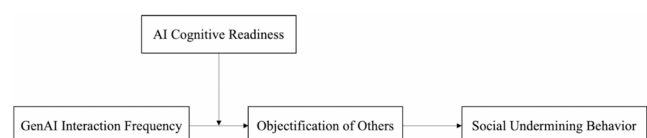


Fig. 1 Theoretical model

were collected at three distinct time points over a one-month period (March 7 – April 4, 2024), strategically aligned with the academic calendar to avoid exam periods and major holidays. A 14-day interval between waves was implemented to minimize confounding effects from short-term disruptions, such as policy changes or academic stressors. To enhance data reliability and validity, we implemented real-time data quality control measures during the data collection process. Responses with highly unrealistically short or excessively long completion times were flagged and excluded. Additionally, highly repetitive or patterned responses were identified and removed to minimize inattentive answering. Only fully completed surveys were retained for analysis, ensuring consistency across the three-wave design.

At Time 1 (March 7, 2024), we distributed the first survey to 561 college students, measuring GenAI interaction frequency and AI cognitive readiness in their daily academic activities. A total of 441 completed questionnaires were received, reflecting a response rate of 78.6%. Two weeks later, at Time 2 (March 21, 2024), the second survey measured the degree of objectification of others. A total of 386 completed questionnaires were returned, with a response rate of 87.5%. At Time 3 (April 4, 2024), the final survey measured participants' social undermining behavior. In this wave, 351 fully completed questionnaires had been returned, with a response rate of 90.9%. The overall response rate was 62.6%.

Participants younger than 18 years of age were excluded from the analyses. The final sample consisted of 315 undergraduate students, of whom 42.2% were male. Participants ranged in age from 18 to 27 years ($M=22.356$, $SD=2.896$), and they represented a variety of disciplines.

Measures

All measures used in this study were adapted from validated scales published in well-known international journals. The original scales were translated into Chinese in collaboration with bilingual team members, following the translation/back-translation method (Brislin, 1980) to ensure linguistic and conceptual equivalence. All items were rated on a 5-point Likert-type scale (1 = strongly disagree, 5 = strongly agree).

GenAI interaction frequency The frequency of participants' engagement with Generative AI (GenAI) was measured using a 3-item scale developed by Tang et al. (2023). We modified it to fit the context of student interactions in educational settings. The scale assessed how often students interacted with GenAI over the past few days in both academic and daily life contexts. An example item is "I used

generative AI to complete most of my academic tasks." The Cronbach's α coefficient for this scale was 0.926.

Objectification of others Objectification of others was measured using a 7-item scale from Belmi and Schroeder (2021), which evaluates the extent to which participants view others in instrumental terms, valuing people based on their utility. We modified it to fit the context of student interactions in educational settings. An example item is "I judge the value of someone mostly based on what he/she can do for me." The Cronbach's α coefficient for this scale was 0.880.

Social undermining behavior We adapted a 3-item scale originally used to measure social inhibition behavior in Britton (2012), modifying it to fit the context of student interactions in educational settings. An example item is "I am unwilling to share knowledge with others in my studies." The Cronbach's α coefficient for this scale was 0.880.

AI cognitive readiness We measured participants' AI cognitive readiness using a 5-item scale developed by Wang et al. (2023), modifying it to fit the context of student interactions in educational settings. An example item is "I understand how artificial intelligence technology is trained and utilized in studies." The Cronbach's α coefficient for this scale was 0.914.

Control variables Following previous research on social undermining and objectification (Belmi & Schroeder, 2021; Britton, 2012), we included age, gender, grade level, and major as control variables. The inclusion of these control variables in the analysis process did not substantially change the results.

Data analysis

We conducted statistical analyses using IBM SPSS Statistics (Version 22.0) for data screening and preliminary analyses, and Mplus (Version 7.4) for structural equation modeling. First, we performed preliminary analyses, including calculating means, standard deviations, correlations, and Cronbach's α to assess the reliability of the measures. Second, we evaluated the measurement model through confirmatory factor analysis (CFA) to verify the hypothesized four-factor structure. Third, to test our hypotheses, we employed hierarchical regression analyses for moderation testing and bootstrapping techniques (5,000 resamples) for mediation analyses, following Preacher and Hayes (2008). Moderation effects were further examined using simple slope tests, with the moderator variables mean-centered before creating interaction terms to mitigate multicollinearity concerns.

The variables used in the analyses remained unstandardized (except for moderation analyses).

Results

Descriptive statistics and correlational analysis

Table 1 presents the means, standard deviations, correlations and reliabilities for all study variables. As hypothesized, GenAI interaction frequency was positively correlated with objectification of others ($r=0.264$, $p<0.01$) and social undermining behavior ($r=0.337$, $p<0.01$). Additionally, objectification of others was positively correlated with social undermining behavior ($r=0.345$, $p<0.01$), providing initial support for our hypotheses.

Confirmatory factor analyses

Confirmatory factor analyses (CFA) were conducted to assess the measurement model, which included four factors: objectification of others, social undermining behavior, GenAI interaction frequency, and AI cognitive readiness. The results (see Table 2) showed that the four-factor model provided a better fit to the data ($\chi^2/df=2.406$, CFI = 0.953, TLI = 0.944, RMSEA = 0.067) than alternative models. All indices met established thresholds for good fit (CFI/TLI > 0.95, RMSEA < 0.08; Hu & Bentler, 1999). By contrast, the one-factor model showed a poor fit ($\chi^2/df=19.859$, CFI = 0.334, TLI = 0.245, RMSEA = 0.245). This confirms the distinctiveness of the

constructs and suggests that common method bias is not a significant concern.

Hypotheses testing

H1: Direct effect

As showed in Table 3, after controlling age, gender, discipline and grade, GenAI interaction frequency had a significant and positive effect on social undermining behavior ($\beta=0.326$, $p<0.01$; Model 2). Thus, H1 was supported.

H2: Mediation effect

GenAI interaction frequency had significant positive effects on both social undermining behavior ($\beta=0.326$, $p<0.01$, Model 2) and objectification of others ($\beta=0.240$, $p<0.01$, Model 6). Objectification of others, in turn, had a significant positive effect on social undermining behavior ($\beta=0.357$, $p<0.01$, Model 4). When objectification of others was included in the model (Model 3), the positive direct effect of GenAI interaction frequency on social undermining behavior decreased (from $\beta=0.326$, $p<0.001$ to $\beta=0.256$, $p<0.001$), indicating partial mediation (Baron & Kenny, 1986). Bootstrapping results further indicated a significant indirect effect of GenAI interaction frequency on social undermining behavior via objectification of others (*indirect effect* = 0.052, 95% CI = [0.0230, 0.0871]). Thus, H2 was supported.

Table 1 Descriptive statistics and correlation analysis

Variables	M	SD	1	2	3	4	5	6	7	8
1. Age	22.356	2.896	—							
2. Gender	1.578	0.496	-0.090	—						
3. Discipline	7.244	3.737	-0.030	-0.051	—					
4. Grade	2.371	1.082	-0.020	-0.099	-0.110	—				
5. GenAI interaction frequency	3.502	0.957	0.116*	0.032	0.023	-0.017	—			
6. Objectification of others	3.560	0.697	-0.056	0.047	0.090	-0.010	0.234**	—		
7. AI cognitive readiness	3.701	0.998	-0.066	0.027	-0.043	-0.014	-0.108	0.009	—	
8. Social undermining behavior	3.613	0.706	-0.049	-0.029	-0.037	0.121*	0.315**	0.353**	-0.008	—

Table 2 Confirmatory factor analysis results

Models	χ^2	df	χ^2/df	RMSEA	CFI	TLI
Four-factor model	310.370	129	2.407	0.067	0.953	0.944
Three-factor model	632.049	132	4.788	0.110	0.869	0.848
Two-factor model	1482.645	134	11.065	0.179	0.647	0.597
One-factor model	2902.908	135	19.859	0.245	0.334	0.245

Three-factor model emerged objectification of others and social undermining behavior into one factor. Two-factor model emerged objectification of others, social undermining behavior and GenAI interaction frequency into one factor. One-factor model emerged objectification of others, social undermining behavior, GenAI interaction frequency and AI cognitive readiness into one factor

Table 3 Results of hypotheses testing

Variables	Social undermining behavior				Objectification of others		
	M1	M2	M3	M4	M5	M6	M7
Control variables							
Age	-0.044	-0.083	-0.060	-0.026	-0.049	-0.078	-0.066
Gender	0.036	0.021	0.011	-0.019	0.047	0.037	0.037
Discipline	-0.023	-0.032	-0.057	-0.056	0.091	0.084	0.091
Grade	0.121*	0.123*	0.122*	0.120*	0.004	-0.005	0.009
Independent variable							
GenAI interaction frequency		0.326**	0.256**			0.240**	0.239*
Mediator							
Objectification of others			0.296**	0.357**			
Moderator							
AI cognitive readiness							0.040
Interaction term							
GenAI Interaction frequency * AI cognitive readiness							-0.166**
R ²	0.019	0.123	0.205	0.144	0.013	0.070	0.098
ΔR^2	0.019	0.104	0.082	0.125	0.013	0.057	0.027
F	1.470	8.706**	17.468**	12.227**	1.031	4.628**	4.770*

N = 315; **p* < 0.05, ***p* < 0.01

H3: Moderation effect

To test the moderating role of AI cognitive readiness, we estimated a regression model including the main effects of GenAI interaction frequency (IV) and AI cognitive readiness (moderator), as well as their interaction term (IV $\times$ moderator). The interaction coefficient between AI cognitive readiness and GenAI interaction frequency was statistically significant ($\beta = -0.166$, $p < 0.01$; Model 7). We applied Edwards and Lambert's (2007) approach to test the indirect effects of GenAI interaction frequency on social undermining behavior at two levels of AI cognitive readiness (i.e. +1 *SD* and -1 *SD*). Simple slope analysis (see Fig. 2) indicated that GenAI interaction frequency was positively associated with objectification of others when AI cognitive readiness was low (-1 *SD*; $\beta = 0.291$, $p < 0.001$), but became nonsignificant when AI cognitive readiness was high (+1 *SD*; $\beta = 0.058$, $p = 0.303$). This indicates that AI cognitive readiness buffers GenAI's effect on objectification of others. Therefore, H3 was supported.

H4: Moderated Mediation

Based on 5,000 resamples, the results showed that the indirect effect of GenAI interaction frequency on social undermining behavior was significant when AI cognitive readiness was low (-1 *SD*; indirect effect = 0.0872, 95% CI = [0.0458, 0.1364]), but not significant when AI cognitive readiness was high (+1 *SD*; indirect effect = 0.0173, 95% CI = [-0.0240, 0.0600]). Thus, H4 was supported.

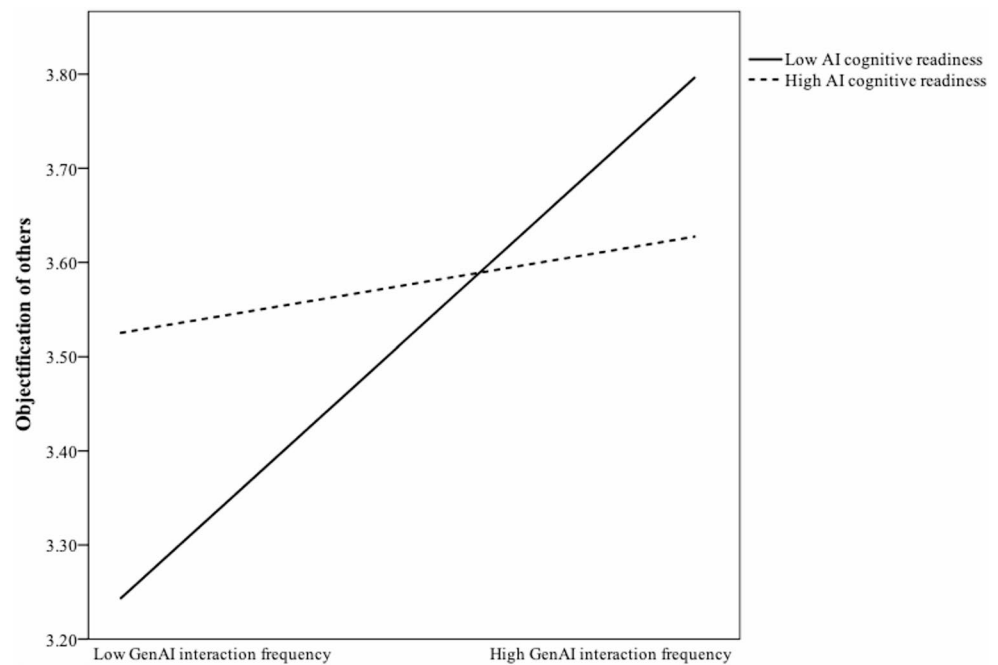
Discussion

While the positive effects of GenAI usage among college students have been widely recognized (Chan & Hu, 2023), less attention has been given to its potential downsides, particularly its influence on interpersonal behaviors such as social undermining. Grounded in Social Cognitive Theory, we investigated how frequent interactions with GenAI foster objectification of others, contributing to social undermining behavior, and how AI cognitive readiness moderates these effects. Our findings add to a growing body of work on AI-human interaction spillover effects (Brinkmann et al., 2023; Zhang et al., 2025; Yang et al., 2025; Hou et al. 2025b). While prior studies have examined how AI interaction influences individuals' prosociality (Zhang et al., 2025), help-seeking (Hou et al., 2024) and workplace behavior (Tang et al., 2023; Yang et al., 2025), our study expands this perspective by showing how repeated GenAI interaction in academic contexts shapes students' interpersonal cognition and social behaviors.

Theoretical implications

First, we extend social cognitive theory by showing that human-AI interactions can influence not only individuals' attitudes toward AI but also their interpersonal behavior in human-AI interaction contexts. While prior research has primarily focused on how users perceive and evaluate AI systems (Cadario et al., 2021; De Freitas et al., 2023), emerging evidence emphasizes that AI interactions may shape broader behavioral patterns (Brinkmann

Fig. 2 The moderating effect of AI cognitive readiness



et al., 2023; Hou et al., 2024; Zhang et al., 2025; Yang et al., 2025). Building on SCT's premise that behaviors are learned through interaction with the environment (Bandura, 1986, 1999), our study shows that frequent interaction with GenAI is associated with greater objectification of others, which in turn correlates with increased social undermining behavior. Rather than learning through imitation, users may internalize the instrumental nature of GenAI interactions, which are typically directive, one-sided, and emotionally neutral. This internalization may then carry over to interpersonal contexts, encouraging individuals to treat others in a more utilitarian and depersonalized manner. By framing GenAI as a non-human yet socially influential interaction partner, we challenge the human-centered assumptions of traditional social cognitive theory and demonstrate how it can be extended to explaining social learning in digital environments. Our findings align with and extend Zhang et al. (2025) by showing that GenAI's influence is not limited to moral decision-making but also shapes interpersonal perceptions and behaviors. Thus, our research expands SCT's applicability to digital environments and highlights GenAI's potential to shape downstream social behavior.

Second, we introduce objectification as an acquired cognitive tendency that helps explain how patterns of human-AI interaction spill over into human-human interactions. Objectification, particularly in the form of instrumentality—where individuals are valued primarily for their utility (Nussbaum, 1995)—has traditionally been examined in moral, sexual, and interpersonal contexts (Fredrickson & Roberts, 1997; Andrighetto et al., 2017). Our study identifies GenAI interaction frequency as a novel antecedent

of objectification tendencies among university students. Specifically, GenAI's outcome-oriented and emotionally neutral interaction style may gradually desensitize users to the autonomy and emotional needs of others, fostering an instrumental view of human relationships. Such effects may stem from GenAI's design, which prioritizes efficiency over emotional engagement, which may reduce users' sensitivity to others' subjective experiences (Harrell & Traeger, 2025). For instance, students who routinely interact with emotionally neutral AI systems may become less inclined to empathize with peers, potentially leading to dismissiveness or reduced responsiveness in interpersonal settings. Supporting this interpretation, Yang (2025) found that workplace interaction with service robots increased employee objectification, which in turn reduces helping behavior. While the interaction context differs, both studies suggest that interactions with non-human agents can foster objectifying social cognition. Our findings thus apply the concept of objectification to illuminate socio-cognitive effects of human-AI interactions, and highlighting the need for further research on how GenAI interactions reshape foundational social processes (Hou et al. 2025b).

Third, we identify AI cognitive readiness as a moderating factor. In line with SCT's emphasis on cognitive factors in regulating behavior, we found that students with higher levels of AI cognitive readiness—those who understand GenAI's logic and limitations—were less likely to exhibit objectification following GenAI interaction. For example, recognizing that GenAI prioritizes semantic coherence over factual accuracy (Ferrara, 2024) may help users maintain conceptual boundaries between machine and human

communication, thereby resisting the spillover of instrumental norms. This finding supports prior research (Wang et al., 2023) and underscores the importance of understanding technology to navigate its challenges effectively. High AI cognitive readiness appears to enable students to critically evaluate AI's influence rather than passively absorb its patterns and mitigate its unintended cognitive and behavioral "spillovers".

Practical implications

Our findings offer several important insights for educators and university administrators. First, since students with higher AI cognitive readiness are less likely to objectify others or engage in social undermining, institutions should prioritize targeted training programs. To mitigate the negative spillover effects of GenAI use, universities should incorporate AI literacy into existing curricula, include modules on GenAI's operational logic, limitations, and ethical dimensions (Ng et al., 2021; Yan et al., 2024). For example, Project-based learning activities that require students to critically evaluate AI-generated responses versus human-generated content can highlight GenAI's utilitarian logic and reinforce distinction between human and non-human interactions, encourage more mindful engagement with AI-driven tools.

Second, strengthening ethical education can encourage students to reflect on the social impact of technology, countering the instrumental view of others fostered by GenAI (Borenstein & Howard, 2021; Wiese et al., 2025). Case-based discussions involving algorithmic bias, misinformation can help develop students' ethical reasoning and social awareness. These activities, when integrated with experiential learning, can promote deeper understanding of appropriate interpersonal norms and reduce the spillover of depersonalized thinking into human relationships.

Finally, universities should proactively support students' emotional and social development to mitigate GenAI's potential isolating effects (Tang et al., 2023) or interpersonal tensions that may arise from GenAI's increasing role in students' academic and social lives (Hou et al. 2025a). Encouraging collaborative learning, peer mentorship, and open discussions about AI use can help preserve a sense of community, further reduce objectification tendencies and social undermining.

Limitations and future research directions

Although our hypotheses were supported, we acknowledge several limitations in our study, which suggest avenues for future research. First, our sample is limited to Chinese university students, which may restrict the generalizability of

the findings. Future research should explore how interaction with GenAI affects college students in other cultural contexts to determine whether the results hold across different populations.

Second, while we applied SCT to examine how objectification of others functions as a learned cognitive process from GenAI interactions, the results indicate that objectification only partly mediate the relationship between interaction with GenAI and social undermining behavior. This suggests that other mechanisms may also play a role. For instance, GenAI use may also undermine users' social skills by limiting opportunities for meaningful human interaction (Hou et al. 2024, 2025a, b). Future research could explore additional cognitive and emotional mechanisms as mediators, such as moral disengagement (Bandura, 1999) or empathy erosion (Decety & Cowell, 2014), which may help to further explain the pathway from GenAI interaction to negative social outcomes. A multi-path mediation model (Preacher & Hayes, 2008) could offer a more comprehensive understanding of these processes.

Third, this study primarily focused on AI cognitive readiness as a moderator, consistent with SCT's emphasis on cognitive factors shaping behavior. However, other factors may also influence the relationship between GenAI interactions and objectification. Future research could investigate the role of individual characteristics (e.g., self-regulation, reflective thinking) and contextual factors (e.g., institutional policies) as potential moderators.

Finally, this study did not measure the specific time-of-day when students interacted with GenAI, a factor that could potentially influence cognitive processing and behavioral outcomes. Prior research suggests that cognitive and emotional states fluctuate throughout the day, with executive function and impulse control diminishing as cognitive resources are depleted (Baumeister et al., 1998). Future research should explore whether late-night GenAI interactions disproportionately affect objectification tendencies and social undermining behaviors.

Conclusion

The findings of this research have shown the probable dark side of GenAI for social interactions among university students. Grounded in Social Cognitive Theory, our analysis shows that frequent interaction with GenAI may foster objectification and facilitates social undermining behavior among university students. Specifically, this effect is strongest for students with lower levels of AI cognitive readiness.

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Data availability The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Declarations

Ethics Approval Ethical review and approval were waived for this study because it involved an anonymous questionnaire survey. The study did not collect any personal identifying or sensitive information, posed no foreseeable risk to participants, and was conducted without commercial interests. In accordance with Article 32 of the Ethical Review Measures for Life Sciences and Medical Research Involving Humans issued by the National Health Commission of the People's Republic of China, research of this nature does not require ethical review. (The official text of the Measures is available at https://www.gov.cn/zhengce/zhengceku/2023-02/28/content_5743658.htm)

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of the interest.

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