JOURNAL OF
EMERGING INVESTIGATORS

Article

It's better than me: Investigating the psychological risks of AI on self-esteem

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SUMMARY
This study was motivated by increasing concerns over the psychological effects of artificial intelligence (AI) tools on human well-being. Specifically, this study examined the correlation between the use of AI information technology and self-esteem in performance contexts, determining whether AI can function as a source of upward social comparison similar to the existing literature on social media and peer-based comparisons. We hypothesized that frequent use of AI would be associated with lower performance self-esteem due to increased upward social comparison, which refers to comparing oneself with others perceived as more skilled, successful, or better off. Put another way, we hypothesized that people who frequently use AI would tend to compare their own abilities with AI (upward social comparison), therefore experiencing decreased self-esteem related to their skills or competence. This hypothesis was tested using an adult convenience sample. The study employed a survey with a sample of 121 participants and conducted a Pearson correlation test to investigate the relationship. Contrary to expectations, frequent interactions with generative AI platforms like ChatGPT and Gemini did not significantly impact users' performance self-esteem; therefore, the hypothesis was not supported. Nevertheless, the results have hopeful implications. The data suggest that current AI tools may not trigger the same social comparison often seen among people and peers. As such, this study concludes that AI, in its current chatbot form, may not pose a significant threat to performance-related self-esteem.

INTRODUCTION
Scholars have begun to raise questions about the ethics of artificial intelligence (AI) information technology (1, 2). Recent work indicates that the ethical risks and safety implications of generative AI depend strongly on how users engage with it, such as whether it is used as a functional tool or as a conversational agent (3, 4). For example, conversational AI systems may raise ethical concerns related to psychological well-being, as users can develop relational or emotionally oriented interactions with these systems, which may influence self-perception and well-being outcomes over time (5). Additionally, ethical concerns have been raised regarding algorithmic bias in generative AI, as AI-generated responses may reflect normative assumptions or value-laden judgments that could shape users' evaluations of themselves (6). Thus, our research aims to examine the psychological impacts of AI tools like ChatGPT, specifically within the domain of self-esteem. Understanding these psychological effects is important, as self-esteem is closely linked to mental health, well-being, and overall quality of life, particularly among young people, who tend to be frequent users of AI technologies (2, 3, 5). ChatGPT became publicly available on November 30th, 2022 (7). Notably, ChatGPT was nearly immediately integrated into education classrooms upon its arrival. According to a 2025 report published by the Pew Research Center, 13% of U.S. teens aged 13 to 17 reported using ChatGPT for schoolwork in 2023, but by 2024, this doubled to 26% (8). These developments raise important questions about how interactions with AI may influence psychological processes, particularly those related to self-perception and evaluation.

There is compelling evidence that adolescents, college students, and members of higher education alike use AI to aid in their academic work. A 2024 survey by the Digital Education Report examined how students in bachelor's, master's, and doctoral programs use AI for their schoolwork, commonly for looking up information, checking grammar, summarizing texts, paraphrasing, and drafting initial versions of assignments (9). Similarly, a national survey by Common Sense Media and Hopelab found that teens and young adults turn to generative AI to gather information and to brainstorm ideas (10). Recent academic studies further report high rates of AI usage among students and adolescents in educational contexts (11, 12). Taken together, these findings indicate that AI is not only widely adopted but frequently integrated into tasks that are closely tied to academic competence and performance evaluation (9, 10, 11, 12). As such, repeated interaction with AI in these contexts may shape how users assess their own abilities, making it important to consider the potential psychological implications, including effects on self-esteem.

In psychology, the social comparison theory broadly captures various types of comparisons, and one such concept is known as upward social comparison (13). According to the American Psychological Association, upward social comparison is the phenomenon in which individuals compare themselves with someone else on various facets such as appearance or abilities (13). Although there is contesting evidence that upward comparison may lead to positive mental health outcomes, preceding research indicates that upward social comparison, especially among adolescents, generally leads to negative perceptions of the self-concept (14, 15). For instance, a study found that people who are outperformed in certain aspects (e.g., on intelligence tests, socially attractiveness, physically attractiveness) tend to rate the outperformer as more intelligent than neutral observers do (16). This phenomenon, known as the "genius effect," stems

https://doi.org/10.59720/25-237

from self-protective processes. In other words, individuals who are outperformed tend to exaggerate the ability of the person who outperforms them, rating them more favorably than neutral observers (16). This pattern suggests that individuals may protect their own sense of competence by attributing their lower performance to the exceptional ability of others rather than to their own shortcomings (16). Likewise, with the rising popularity of AI, we theorized that AI and Large Language Models, like ChatGPT and Gemini, may create similar opportunities for upward social comparison of one's abilities not with peers but with AI platforms themselves. As AI systems are often perceived as exhibiting high levels of competence across domains such as writing, reasoning, and problem-solving, comparisons with AI may become another form of performance evaluation relevant to self-esteem.

Importantly, there is emerging evidence that engagement with evaluative systems can influence self-perceptions, particularly individuals' self-esteem (17). Insights into these processes can be drawn from research on how evaluative feedback and social comparison affect self-esteem, such as studies conducted in the context of sports (17). Bardel et al. examined fluctuations in athletes' state self-esteem in relation to perceived performance and social comparison among competitive athletes (n = 95), demonstrating that self-esteem was more strongly influenced by athletes' evaluations of their own competence relative to others than by objective match outcomes (17). Athletes reported higher self-esteem following performances they perceived as successful and lower self-esteem following performances evaluated negatively, indicating that competence-related self-assessments play a central role in shaping self-esteem (17). These findings suggest that self-esteem is sensitive to evaluative feedback and comparative judgments, even outside of explicit win-loss framing (17).

In the context of generative AI systems such as ChatGPT, similar self-evaluative processes may occur. Interacting with AI systems that consistently generate highly advanced responses may function as a comparison benchmark, prompting users to evaluate their own abilities in relation to the system's perceived competence. As AI systems are often perceived as exhibiting what we term "supercompetence," defined here as consistently high-level performance across domains such as writing, reasoning, or creativity, such upward comparisons may elicit doubts about one's own abilities, mirroring the self-evaluative mechanisms observed in social comparison research.

Generalizing these results of previous scholarly works, we suspect that AI's perceived supercompetence has the potential to make people feel worse about their own abilities as AI can outperform users, especially in skill-based domains like writing and coding. Thus, we hypothesized that more frequent AI use would be associated with lower levels of self-esteem as a result of increased upward social comparison with AI. Individuals who use AI information technology will have more opportunities to engage in upward social comparison, specifically comparing one's own ability to that of AI, and thereby experience a decrease in self-esteem. For ethical and feasibility reasons, our study uses a quantitative questionnaire survey that recruited consenting adult participants from an online research platform (Prolific). Although broader concerns motivating this work relate to adolescent AI use, our research examines these questions within an adult convenience sample. Findings are therefore interpreted primarily in the context of adult users, while potential implications for adolescent populations are discussed conceptually rather than as direct empirical conclusions. Our results indicated that there was no significant correlation between AI usage and performance self-esteem, and AI usage was not associated with upward social comparison. However, upward social comparison was significantly associated with lower performance self-esteem, suggesting that social comparison remains an important predictor of self-esteem even if AI usage itself does not appear to trigger it.

RESULTS

To investigate whether frequent AI use is associated with lower performance self-esteem and greater upward social comparison, participants completed survey questions measuring AI usage frequency, performance self-esteem, and upward social comparison. There was a total of 121 participants, and among these participants, 20% were high school graduates, while over 75% were individuals with a bachelor's degree or in a bachelor's program (**Table 1**). Each participant answered Likert-scale questions about how often they use AI, their self-esteem levels, and the degree to which they engage in upward social comparison. We used Pearson correlations to examine relationships among AI usage, upward social comparison, and self-esteem.

First, we examined the association between AI usage and upward social comparison because we had theorized that people who depend more on AI may be more likely to engage in social comparison. Before conducting the Pearson's correlation test, we examined the distribution of AI usage by visualizing the frequency of responses across usage categories, which indicated substantial variation in how frequently participants reported using AI (**Figure 1**). Similarly, we examined the distribution of social comparison scores, which showed substantial variability across participants and responses spanning the full range of the scale (**Figure 2)**. We observed no obvious upward or downward correlation (**Figure 3**). The Pearson's correlation test indicated no significant relationship between AI usage frequency and upward social comparison (r = .011, p = .904).

Secondly, we examined the association between upward social comparison and performance self-esteem. We had theorized that people who engage in greater amounts of upward social comparison would have a lower self-esteem. Before conducting the Pearson's correlation test, we checked whether our responses were representative of the population by creating a simple histogram that shows the distribution of responses for self-esteem levels, and we observed moderate variation in the self-esteem levels among our participants (**Figure 4**). In the analysis, we found a slightly negative correlation between upward social comparison and performance self-esteem (**Figure 5**). Specifically, the results of Pearson's correlation test reported a slight negative correlation (r = -.293), and the finding was statistically significant (p = .0001), which suggests that people who engage in more upward social comparison tend to have lower self-esteem on average. This negative correlation between

https://doi.org/10.59720/25-237

Demographic categories	Frequency	Percentage (%)
Gender		
Male	57	0.47
Female	64	0.53
Education		
High School	24	0.20
Bachelor's Degree	93	0.77
Master's Degree	4	0.03
Doctoral Degree	0	0
Age		
18-22	66	0.54
Over 22	55	0.46
Ethnicity		
White / Caucasian	33	0.27
Asian - Eastern	2	0.02
Asian - Indian	4	0.03
Hispanic	3	0.02
African descent	61	0.50
Native-American	0	0
Mixed race	5	0.04
Other	13	0.11
Prefer not to say	0	0
Income		
Less than $25,000	44	0.36
$25,000 - $50,000	32	0.26
$50,000 - $100,000	26	0.21
$100,000 - $200,000	10	0.08
More than $200,000	2	0.17
I prefer not to say	7	0.06
Total	121	100

Table 1: Demographic characteristics of participants. This table indicates the demographic characteristics of the participants (n = 121), displaying their gender, level of education, age, ethnicity, and income.

upward social comparison and performance self-esteem aligns with findings from previous literature (9, 12, 17, 18, 19, 20, 21, 22, 23).

Finally, we conducted a bivariate correlation test for our primary independent and dependent variables: frequency of AI usage and performance self-esteem. We had predicted that people who used AI more would have lower self-esteem. The primary independent variable was measured using the following simple survey question: "How often do you use AI?" (0 = "Never" to 8 = "Hourly or more"). The primary dependent variable was measured via the State Self-Esteem Scale from Heatherton and Polivy containing seven questions (24). The scatter plot appears to show a near zero negative correlation (r = -.039), and the finding was not statistically significant (p = .675), suggesting that there is no evidence people who used AI more would have lower self-esteem (**Figure 6**). Therefore, our hypothesis was not supported.

https://doi.org/10.59720/25-237

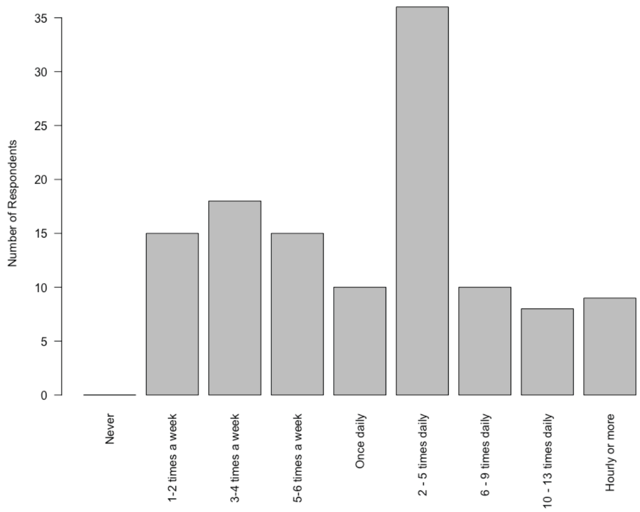

Figure 1: Distribution of AI usage frequency among participants. Participants (*n* = 121) indicated how frequently they used AI by selecting one of several predefined usage categories ranging from 'Never" to "Hourly or more." The bar plot displays the number of respondents within each usage category, illustrating the distribution of AI usage frequency across the sample. Higher values along the x-axis represent more frequent AI use, whereas lower values indicate less frequent or no AI use.

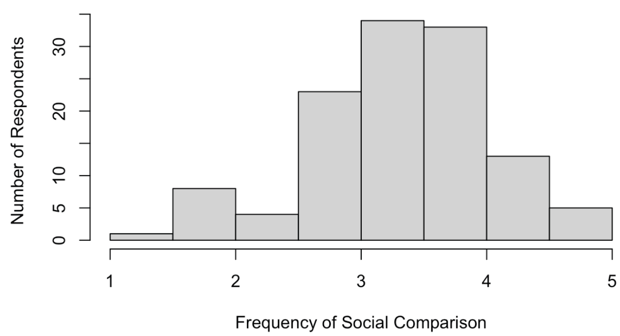

Figure 2: Distribution of the amount of upward social comparison of each participant. Participants (*n* = 121) indicated their amount of social comparison by answering a matrix 5-item Likert scale. The histogram indicates the average social comparison score of each participant. The average performance social comparison score was calculated by taking the sum of their scores for each item and dividing it by the number of items in the questionnaire. Higher values on the x-axis indicate that the individual frequently engages in upward social comparison (i.e., more often compares oneself to others). Likewise, lower values on the x-axis indicate that the individual less often engages in upward social comparison (i.e., less often compares oneself to others).

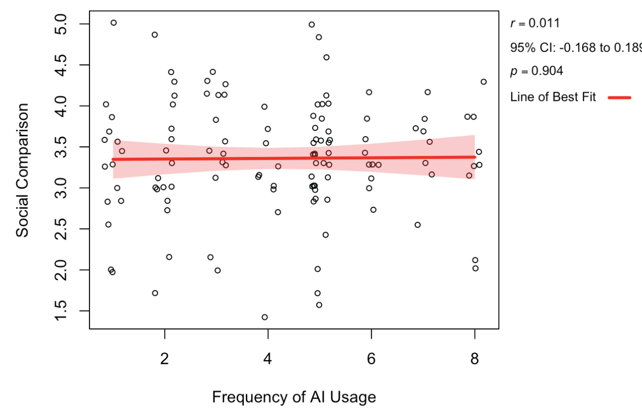

Figure 3: Pearson's r correlation test results for relationship between AI usage and upward social comparison levels (*n* = 121). We found a very weak positive correlation (r = .011) between AI usage and upward social comparison, and the finding is not statistically significant (p = .904). This suggests that there is no trend towards increased AI usage and increased upward social comparison. The shaded area in red indicates 95% confidence levels.

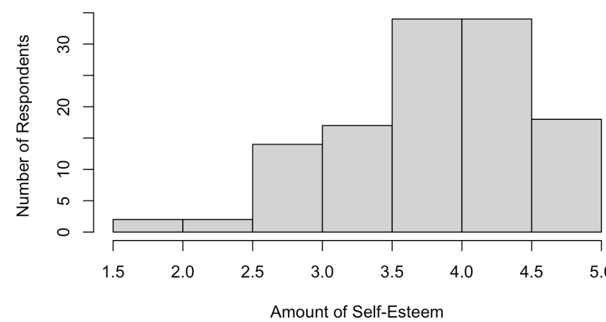

Figure 4: Distribution of the amount of self-esteem of each participant. Participants (*n* = 121) indicated their performance self-esteem by answering a matrix 5-item Likert scale. The histogram indicates the average performance self-esteem score of each participant. The average performance self-esteem score was calculated by taking the sum of their scores for each item and dividing it by the number of items in the questionnaire. Higher values on the x-axis indicate that the individual has a higher performance self-esteem (i.e., more confident in one's own performance). Likewise, lower values on the x-axis indicate that the individual has less performance self-esteem (i.e., less confidence in one's own performance).

DISCUSSION

In this study, we analyzed the relationship between AI usage frequency and self-esteem levels, specifically in the domain of one's performance. In our correlation tests, we found no significant association between increased usage of AI and decreased self-esteem as we had hypothesized. The fact that the correlation was near zero suggests that the frequency of AI usage may not significantly impact individuals'

https://doi.org/10.59720/25-237

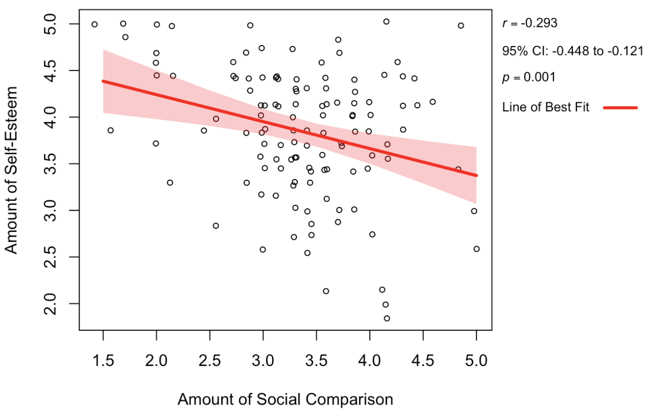

Figure 5: Pearson's r correlation test results for relationship between upward social comparison levels and performance self-esteem levels (*n* = 121). We found a slight negative correlation (*r* = -.293) between upward social comparison and self-esteem, and the finding is highly significant (*p* = .001). This suggests that there is a negative correlation between social comparison and self-esteem, supporting other papers' claims about social comparison and self-esteem. The shaded area in red indicates 95% confidence levels.

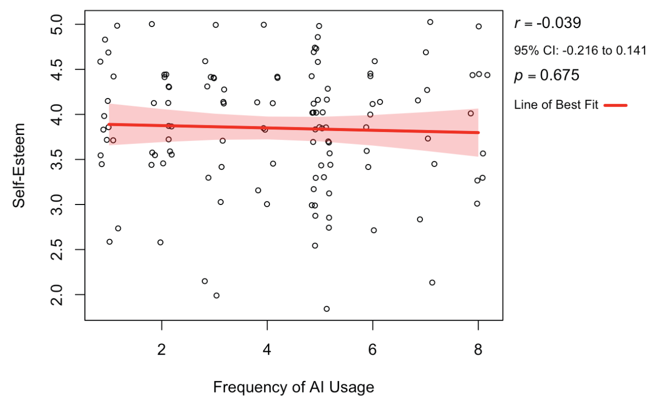

Figure 6: Pearson's r correlation test results for relationship between AI usage and self-esteem levels (*n* = 121). We found a very weak negative correlation (*r* = -.039) between AI usage and performance self-esteem, and the finding is not statistically significant (*p* = .675). This suggests that there is no trend indicating that increased reliance on AI may lead to lower levels of self-esteem. The shaded area in red indicates 95% confidence levels.

self-esteem levels. Additionally, there was no significant correlation between AI use and increased upward social comparison, suggesting that our theory that people who use AI more frequently may be more likely to engage in social comparison was not supported.

One explanation for this finding could be the physical and morphological differences between humans and AI in this case. Wang et al. conducted seven studies and found that participants who were employees at a company reported an increase in perceived job insecurity when the workplace exposed them to more human-like robots (i.e., anthropomorphic) compared to typical robots (18). In the current study, we suggest that such feelings may arise from increased likelihood of upward social comparison. In fact, Jeong et al. found that users who perceived virtual humans as highly anthropomorphic tended to engage in more social comparison, although their study primarily focused on how individuals rate anthropomorphic virtual humans (19). In another study, Yogeeswaran et al. found that participants were less supportive of robots in workspace environments when they were described as highly capable or designed to look human-like (20). In contrast, robots perceived as less anthropomorphic or whose capabilities were unknown were seen as less threatening and received more support (20). Therefore, we recommend that future researchers conduct experiments using anthropomorphic AI or robots.

Another interpretation is that frequent AI users have already adapted cognitively or emotionally to the presence of AI, reframing it not as a competitor but as a collaborative assistant. Research on human-AI interaction suggests that people can form beneficial companion-like relationships with conversational AI, where users report positive social health outcomes and view these systems as reliable conversational partners rather than threats to self-worth (25). Furthermore, related studies on social-oriented communication with AI companions suggests that such interactions can provide various forms of support such as appraisal, emotional, and informational support (26). For this reason, users may value the AI technology without perceiving it as adversarial (26). This reframing could buffer users against any threat to self-concept, especially in performance domains (26). Moreover, given AI's utility and widespread integration into education, students may perceive AI usage as a normative or even intelligent strategy—thereby boosting confidence rather than diminishing it (26).

Lastly, the findings may reflect an early-stage phenomenon. As mentioned before, ChatGPT became publicly available in late 2022. As such, AI is still emerging, and cultural attitudes toward it are not yet fully formed. These attitudes may also differ across age groups, as younger users who, as still developing their academic identity and self-concept, may respond differently to AI than older users. As AI becomes more integrated, and as avatars or agents adopt more human-like forms, future interactions may activate stronger social-comparison processes. Longitudinal studies or studies comparing younger and older populations, as well as those manipulating anthropomorphism and user-AI relational framing, could help test these dynamics.

One key limitation of this study was that the sample was demographically concentrated, with approximately 50% of participants categorized as being of African descent. Because the survey did not collect verified country-of-residence data and did not distinguish between African American identity, African nationality, and other African-descended identities, this demographic category should be interpreted cautiously. This concentration may limit the generalizability of the findings, as cultural background and sociocultural context may influence how individuals perceive, use, and emotionally respond to AI technologies. However, this concern is somewhat mitigated by the fact that no respondents selected "Never" when asked about their AI usage, suggesting that all participants had at least some exposure to AI technologies. Thus, future research should collect more precise demographic and geographic information to better examine whether cultural or regional differences shape the psychological effects of AI usage.

https://doi.org/10.59720/25-237

Additionally, for feasibility reasons, we conducted this study using a survey rather than a controlled experiment, which makes it difficult to draw causal inferences. Therefore, to establish causation, future researchers should conduct experiments, which can help us draw causal inferences and can offer greater internal validity. One idea could be to task participants with a difficult problem, giving the first treatment group the option to use AI, which is provided; requiring the second treatment to use only AI to solve the problem; and limiting the control group from using AI at all. Then, researchers could ask participants a randomized set of questions, some of which ask about their self-esteem levels. This randomization helps reduce demand bias, which is when participants actively change their responses due to their belief about the study's purpose—in this case, if researchers only ask self-esteem questions, participants might associate their experimental task with the purpose of these questions, leading to biased responses (27).

Third, we report the limitation of using one survey question to measure individuals' frequency of AI usage. Future researchers are encouraged to ask multiple layers of the question to ensure quality responses. For example, instead of only asking "How often do you use AI?" researchers can ask additional questions about how often they use a specific AI platform (e.g., ChatGPT, Gemini, etc.).

Fourth, potential outliers were assessed prior to analysis (**Table 2**). First, the empirical rule for approximately normally distributed data suggests that roughly 95% of observations are expected to fall within ±2 standard deviations of the mean (24). Using this criterion, the sample mean was 182.96 and the sample standard deviation was 107.58, yielding a ±2 standard deviation range of -32.20 to 398.12. All observed values fell within this interval. It is acknowledged that standard deviation-based thresholds rely on assumptions of approximate normality and can be sensitive to skewed distributions and extreme values. Accordingly, the ±2 standard deviation criterion was used solely as a descriptive screening tool rather than as an automatic exclusion rule (29). Given that no observations exceeded this threshold and that all values were considered plausible within the context of the measured variable, no data points were excluded. All 121 participants were therefore retained for analysis.

Studies show that adolescents are particularly susceptible to upward social comparison on social media, as frequent exposure to curated and socially desirable peer content can encourage unfavorable self-evaluation and is associated with lower self-esteem and diminished subjective well-being (21, 22, 23, 30). Similarly, exposure to AI-generated content may create another powerful comparison target; individuals may evaluate their own abilities, performance, or creative output against AI, potentially resulting in similar feelings of inadequacy or lowered performance-related self-esteem. Since adolescents are more likely to compare themselves to peers online, and this has been found to be linked to negative self-evaluations, we recommend future researchers to replicate the fundamental aim of this study on a sample of adolescents, perhaps in the context of education (22, 23).

In this study, we explored the relationship between AI information technology usage and self-esteem, specifically within performance-related contexts. Contrary to our initial hypothesis, frequent use of AI tools such as ChatGPT and Gemini did not significantly correlate with decreased self-esteem. Our findings suggest that current generative AI platforms may not be viewed as direct benchmarks for personal ability, perhaps due to their lack of human-like characteristics or because individuals have already cognitively reframed AI as supportive rather than competitive. These theories have yet to be tested; therefore, future research should address these important avenues. Lastly, broadening the demographic scope, especially among adolescents in diverse educational settings, could yield insights into how generational and contextual differences shape interactions with AI.

Ultimately, as AI becomes more integrated and sophisticated, continued investigation into its psychological impacts remains essential. Understanding these dynamics will help educators, psychologists, and policymakers better support individuals in adapting to technological advancements, hopefully mitigating potential negative effects on mental well-being.

Item
1. I feel confident about my abilities.
2. I feel frustrated or rattled about my performance.
3. I feel as smart as others.
4. I feel confident that I understand things.
5. I feel that I have less scholastic ability right now than others.
6. I feel like I'm not doing well.
7. I am worried about looking foolish.

1 = "Not at All" 2 = "A Little Bit" 3 = "Somewhat" 4 = "Very Much" 5 = "Extremely"

Table 2: Performance self-esteem questions. This table shows the questions given to our participants to collect data about their self-esteem. This study used questions that assess individuals' self-esteem levels related to performance as adopted from the State Self-Esteem Scale (24). For each question, participants were provided with a 5-item Likert-scale.

MATERIALS AND METHODS

Survey

All survey participants were collected via Prolific, an online research platform. Participants were required to (a) be over 18 years old, (b) have current or recent enrollment in an educational program, and (c) be proficient in English. This allowed for a demographically diverse adult sample while ensuring relevance to the study's focus on AI usage. Prior to data collection, a sample size calculator was used to estimate the minimum number of participants required to achieve adequate statistical power for the planned analyses. Based on this calculation, a target sample size of approximately 121 participants was determined, which was the total of 121 participants completed the survey (31).

The survey was created and hosted in Qualtrics and distributed through Prolific, which has a pre-existing participant pool. The study was not directly advertised to external audiences; instead, participants were recruited through Prolific's internal participant marketplace, where eligible individuals voluntarily opted into the study. Prolific managed participant matching, distribution, and payment. Participants were compensated approximately $0.60 USD upon successful completion of the survey. After data

https://doi.org/10.59720/25-237

collection, responses were downloaded from Qualtrics for analysis. Data were screened prior to analysis as described, and no participants were excluded based on these criteria.

AI Usage Measurement

Before the final survey was administered, a pilot version was conducted with a smaller sample of approximately 40 respondents. In the pilot survey, AI usage was measured using a more detailed question that asked participants how often they used AI for specific tasks, such as searching for information, writing, coding, paraphrasing, brainstorming, checking grammar, creating content, solving quantitative problems, and self-studying. This question was revised and adapted from an existing social media scale to better align with the present study's focus on overall AI usage (32, 33). The pilot version focused too heavily on specific AI-related tasks and use cases, which may not have fully captured participants who used AI in ways not listed. Because the present study focused on overall AI usage frequency rather than the purpose of AI use, the final survey asked: "How often do you use AI (e.g., ChatGPT, Gemini, Claude, DeepSeek, etc.)?" Participants were given nine response options (**Figure 1**). This revision allowed AI usage to be measured more directly as overall frequency of use.

Performance Self-Esteem Measurement

The primary dependent variable is the performance self-esteem. To assess this, we used a subset of the State Self-Esteem Scale by Heatherton et al (24). Seven items were selected that pertain directly to perceived competence and performance. Questions 1, 4, 5, 9, 14, 18, and 19 were extracted and used in this paper's survey (**Table 3**). The others were removed as these were unrelated to performance self-esteem but rather measured other aspects of self-esteem, such as one's appearance. Following the instructions provided by the original scale, participants responded on a 5-point Likert scale (1 = "Not at all" to 5 = "Extremely"). For each participant, responses to the seven items were first summed to produce a total performance self-esteem score ranging from 7 to 35. This total was then divided by 7 to calculate an average performance self-esteem score, resulting in a final score ranging from 1 to 5, with higher values indicating higher performance self-esteem. These average scores were used in all analyses and graphical representations in this study.

Upward Social Comparison Measurement

To test the theory that upward social comparison is correlated with lower self-esteem scores, this study measured another variable, specifically the amount of performance social comparison. This was measured to validate whether people's self-esteem is truly influenced by upward social comparison. The study used questions 2, 3, 5, 6, 8, 9, and 11 from a prior study by Gibbons and Bunk, specifically their Iowa-Netherlands Comparison Orientation Measure (34, **Table 4**). This subset of questions specifically measured the performance social comparison and thus was selected for this survey. Participants responded on a 5-point Likert scale. The same method for calculating the performance self-esteem scores were used to determine the upward social comparison score.

Item
1. I always pay a lot of attention to how I do things compared with how others do things.
2. If I want to find out how well I have done something, I compare what I have done with how others have done.
3. I am not the type of person who compares often with others (reversed).
4. I often compare myself with others with respect to what I have accomplished in life.
5. I often try to find out what others think who face similar problems as I face.
6. I always like to know what others in a similar situation would do.
7. I never consider my situation in life relative to that of other people (reversed).

1 = "I disagree strongly"	2 = "I disagree"	3 = "I neither disagree nor agree"	4 = "I agree"	5 = "I agree strongly"

Table 3: Upward social comparison questions. This table shows the questions given to participants to collect data about the extent to which participants engage in upward social comparison. These questions were adopted from the Iowa-Netherlands Comparison Orientation Measure (30). Each question was assessed with a 5-item Likert-scale.

Analysis

All analyses were conducted in RStudio (Version 025.05.0+496). For the data analysis, the "stats" package was used. Pearson's Correlations were used to examine relationships among AI usage frequency, upward social comparison, and performance self-esteem because the scale-derived variables approximated continuous measures, consistent with common practice in psychological and social science research using multi-item Likert scales (24, 32, 33). Correlation analyses were performed using the "cor.test" function in the stats package, which provided correlation coefficients, 95% confidence intervals, and significance levels. AI usage was treated as a continuous variable across its full range of responses, and average scale scores were used for all variable measures. Descriptive statistics were computed prior to analysis, and all 121 participants were retained for the final analyses. All histograms and scatterplot graphs in this paper were made in RStudio using the histogram and plot functions.

Received: July 1, 2025
Accepted: January 16, 2026
Published: September 7, 2026

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