

# The Impact of Widespread Use of AI-Driven LLMs on Academic Self-Esteem, Loneliness and Cognitive Flexibility of Adolescents

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## ABSTRACT:

The idea of Artificial Intelligence (AI) comes from thinkers like Alan Turing, and the technology itself has permeated daily life in the form of large language models (LLMs). This paper examines the impact of this technology on adolescent development. Technology is widely available to this age group, unlike children; and unlike adults, their cognitive faculties are still developing. Hence, they are an important population to consider. The study examines attitudes toward technology - positive, negative and anxiety about dependence as mediators between AI Use and three outcome variables - academic-self-esteem, cognitive flexibility and Loneliness. The study uses a cross-sectional survey design collecting data from Indian school children (aged 12 to 19, N = 407). The study was pre-registered on OSF. Preliminary reliability analysis for the tools and correlations were conducted. Based on these findings, two mediation models were analysed. Positive attitude towards technology/AI was a full mediator between AI Use and Cognitive flexibility, and academic self-esteem was a partial mediator between cognitive flexibility and loneliness. We also found that anxiety about dependence had a small but significant predictive impact on loneliness through regression analysis. The study has important implications for the study of the impact of AI, as it examines both attitudes and behaviours. Future studies can take up generational differences in use of LLMs, and qualitative approaches to understand how human-AI interactions evolve. The implication of the study for parents and educators is the importance of understanding how technology is used and enhancing literacy to promote use without dependence.

**Keywords:** Adolescent development, education, metacognition, quantitative, technofence

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The phylogenetic origin of Artificial Language and its connection with Language can easily be

traced back to Alan Turing's rule-based symbolic AI and Noam Chomsky's theories of Grammar

during the late 1950s (Cordeschi, 2007). Word embeddings with tools like Word2Vec (2013) and GloVe enabled computation systems to represent words as vectors capturing meaning and similarity. Thereafter, based on the information-processing system inherent in the human brain, the application-based schemas of neural Networks and recurrent neural networks (RNNs) & Long Short-Term Memory networks (LSTMs) enabled the processing of sequences like texts during the year 2000 (Harari, 2024). From 2017 to the present day, the advent of Transformer Architecture (Attention is All You Need) became the backbone of Large Language Models (LLMs). The discoveries postulated that bigger models, bigger data and bigger computations shall always perform better, and thus competing models Google (PaLM, Gemini), Anthropic (Claude), Meta (LLaMA), Mistral and Open AI rushed forward for application-based utility as coding assistants, healthcare, education creative writing, Law and almost all spheres of life which hitherto were under the domain of the Left Brain.

Open sourcing and democratisation of access made the utilisation almost ubiquitous, especially for those who are into the domain of structured learning at schools, colleges and educational institutions. With the introduction of OpenAI's ChatGPT in November 2022 (Marr, 2023), several Artificial-Intelligence (AI) driven Large Language Models (LLMs) like Gemini, DeepSeek and others are used by millions of users every day. Within 5 days, ChatGPT had a million users, and as of May 2025, there are 800 million active weekly users (Duarte, 2025). The widespread availability of such chatbots comes with both benefits and drawbacks. This study investigates the dual impact – beneficial and adverse – effects of AI-driven LLMs on adolescent social and educational development.

### Adolescence

Adolescence is the transitional period between childhood and adulthood, characterised by several physical, cognitive and social changes (Elkind, 1970). Cognitively, Piaget places adolescents in the formal operational stage and believes that children over the age of 12 are capable of abstract

thought and scientific thinking. His sensory-motor explorers have now become little scientists capable of developing hypotheses and testing them through their experiences. But Piaget also discusses two fallacies of adolescence – egocentrism and the myth of invincibility. Elkind (1967) explains that adolescent egocentrism is a result of the capacity of an adolescent to take on others' thoughts. They are unable to discern if their ideas about what others are thinking are true or the result of their own preoccupations. He writes that "it is this belief that others are preoccupied with his appearance and behaviour that constitutes the egocentrism of the adolescent" (p.1030). The second fallacy is the perception of invincibility that leads to increased risk-taking behaviour (Elkind, 2025). Adolescents also suffer at the clutches of the imaginary audience due to their new skill of understanding (or failing to understand) others' cognitions, what is known as a "personal fable" – the complex belief in the uniqueness of their feelings, which is mostly untrue.

These concepts emphasise the importance of adolescent social development. Understanding how to respond to others and interact with the environment is an important part of adolescent development. Early adolescents may need time to sort out their identity concerns and may step back from their social relationships (Larson, 1997). Distance from parents may also increase as the importance is given to peer relationships (Larson, Richards, Moneta, Holmbeck, & Duckett, 2013).

### Adolescents and technology

Adolescent development carries key developmental milestones like identity formation and cognitive advancements in abstract thought. The Prefrontal cortex is in its formative stage at this time (Crone & Steinbeis, 2017). The availability of LLMs and their ready-made answers could jeopardise the individual sense of reasoning and the development of their own voice. Cognitive flexibility is "the ability to quickly reconfigure our mind, like when we switch between different tasks" (Braem & Egner, 2018, p. 470). Neural studies show the

involvement of reward pathways and areas like the anterior insula (Hauser et al., 2015), and these pathways are still developing and much inferior to the circuits in adults (Giller, Zhang, Roessner, & Beste, 2019). Çelikkaleli (2014) found that cognitive flexibility was positively correlated with academic, social and emotional self-efficacy.

A 2020 study in the United States pointed out that 95% of adolescents (aged 428-444) have internet access, 67% own their own mobile phone, and 68% have a social media account (George et al., 2020). The study examined the difference based on economic background and found that youth from economically disadvantaged families, while having access to digital technology to the same extent, reported more negative experiences online. Several studies also link adolescent technology use with physical ill-health (Mateo-Orcajada et al., 2023; Rosen et al., 2014).

A 2019 study pointed out that the association between adolescent well-being and digital technology use is small and doesn't warrant as much alarm as most people think (Orben & Przybylski, 2019). However, most researchers agree that digital technology use in adolescence comes with risks – including higher exposure to bullying and psychological consequences like anxiety, depression and loneliness (Moreno et al., 2011).

Kraut and others, as early as 1998, point out that the time adolescents spend on technology comes out of real-life activities that are cognitively or socially enriching (Kraut et al., 1998). However, a more recent Japanese study (Colwell & Kato, 2003) pointed out that the preference for playing video games over spending time with friends was unrelated to friendship quality, and Durkin and Barber (2002) found that video-gaming adolescents had higher levels of family closeness and attachment to school than non-gamers. Hence, the time spent on technology need not be negative, but could give adolescents a way to achieve flow and personal contentment (Weibel et al., 2008). There are also some interesting studies on the effect of digital technology on self-esteem. Davis (2013) found that students who contacted their friends online had higher friendship quality

and also greater self-concept clarity. Other studies show that anxiety and alienation can develop through engagement in the online environment (Charmaraman et al., 2018).

Adolescence is a period during which there is a renegotiation of relationships, and technology can either facilitate or deteriorate the quality of these relationships.

### Impact of AI

Research in 2019 showed that interactions between children and AI could alter the child's perception of their own intelligence (Howley III, 2019). Some researchers point out that AI can replace mundane tasks and create opportunities for adolescents to engage creatively and with tasks involving empathy (Arees, 2023).

In terms of critical thinking and attention span, AI seems to be a hindrance to adolescent educational and cognitive outcomes. A key term that has emerged in the literature in recent years is “digital amnesia” – the tendency of individuals to rely excessively on technology for storing and accessing information (Dirin, Alamäki, & Suomala, 2019). Yan (2020) found that this weakens cognitive ability – comprehension and unaided recall. Kosmyna and their colleagues (2025) pointed out that the use of LLMs diminished learners' engagement and diminished deep learning. When students do not rely on LLMs, they report greater commitment to understanding the task and more mental effort, suggestive of self-regulated learning; further, longer focus and strategic flexibility were also observed (Georgiou, 2025). Dubey and others (2024) worry that overdependence on ChatGPT may lead to the loss of critical executive functions like writing. Their review also showed that sustained attention, planning, and creativity may also be adversely affected. A neuroimaging study showed that using an LLM to write an essay lowered the ability to quote from the essay, lowered perceived ownership, and lowered attentional engagement and strategic integration (Kosmyna et al., 2025). A recent review paper found that while ChatGPT can be used to enhance critical thinking by generating ideas and getting feedback, over-dependence on the tool

can impair the development of critical thinking and reduce motivation to delve deeper into the information to analyse (Melisa et al., 2025). Lin and Chen (2024) explored the effect of AI-integrated education on college students and found that it had both positive and negative impacts. On one hand, AI could enhance engagement and stimulate creativity, but on the other hand, it caused emotional disengagement with the content and increased performance anxiety.

Several studies have examined what is called the “Janus Effect” of generative AI. Zhan et al (2024) discuss its dual impact on creativity and human dignity. Susarla et al. (2023) strongly point out that knowledge acquisition has changed in light of AI tools and research activities, and education has changed. However, they also point out that it was once thought that calculators would make students forget arithmetic. Hence, the use of AI to replace thinking is an unfounded fear. These scholars and others like Netzer (2024) suggest that use of such tools in scholarly work should be governed by some guidelines and codes of conduct within the community.

Rodríguez-Ruiz et al. (2025) found that self-control was a significant predictor of AI-technology (AIT) use, as AIT could respond to a self-imposed request, covering the need for socialisation. Higher self-esteem was linked to lower use of AIT to interact with others. Hence, self-esteem also influences how or whether AI is used for social needs. The study also found that low self-efficacy was linked to more dependence on AI for academic tasks and less learning engagement. A qualitative study examined student motivations in using generative AI for learning (Pavone, 2025) and found that AI helped increase self-efficacy and clarity of concepts and helped generate new ideas. Drawbacks were loss of autonomy and fear of dependence, fear of automation and decreased legitimacy. The quantitative phase of the study found that self-esteem was positively linked to AI-enhanced academic performance, AI-enhanced creative thinking and AI enjoyment and negatively correlated with legitimacy concerns and fear of automation.

Lai and others (2023) found that AI education had a negative impact on adolescents’ social adaptability, and family support mediated the role between AI education and social adaptability. They stress that adolescents are key recipients and users of AI, and as their social environment influences them profoundly (Lu et al., 2020), the impact of AI on social development needs to be examined carefully.

### **Technology and Loneliness**

It is also interesting to see a growing body of literature on loneliness and the impact of technology, particularly after the COVID-19 Pandemic. Loneliness is termed the hidden pandemic (Pricolo, 2025) with immense impact on physical and psychological health (Blundell, 2024). While technology offers all-time connectivity, there is evidence that technology-aided interactions did not adequately substitute for lost physical contact. Patulny and Bower (2022) said that social network “pruning” occurred during and after the lockdown across all age groups in different forms. Another interesting study found that social loneliness was greater in older adults, while physical loneliness was more in younger participants (Landmann & Rohmann, 2022).

Apart from some evidence on technology not alleviating loneliness, we also have evidence that technology can induce social isolation. A 2024 study found that online vigilance and phubbing were correlated with loneliness and moral disengagement (Maftei & Măirean, 2024). Phubbing is a form of techno-ference that seems to be prevalent among youth, and this study said it was predicted by loneliness and online vigilance.

With the rise of AI, technologies to combat loneliness based on Artificial intelligence have also been developed. Taebnia (2025) did a conceptual analysis and identified two frameworks for conceptualising AI companionship – an anthropocentric perspective examining the ability of AI to provide meaningful companionship from a human point of view and the constructivist approach where the Human-AI interaction is



seen as a dynamic relationship where meaning is constantly created. The author suggests that AI's increasing prevalence can reshape the view of "reliable functionality" in two ways: (i) it can reinforce a utility-driven perspective or (ii) expand our vision beyond mutual advantage and foster human-AI relations by looking at technology as independent entities. Sullivan et al (2023) developed an AI-based emotional support model that was tested over 2 years. They found that there was a mix of positive and negative characteristics as they extracted 5 positive (i.e., perceived humanness, perceived emotional support, perceived AI's friendship, perceived (less) loneliness, and mental health benefits) and four negative themes (i.e., perceived lack of conscientiousness, perceived incredibility, perceived violation of privacy, and perceived creepiness of AI). A recent systematic review identified that AI-driven technology could deliver personalised and cost-effective interventions to reduce loneliness in older adults through emotional stimulation, speech recognition and adaptive capabilities with a potential for fostering meaningful engagement (Yang, Wang, Xiang, & An, 2025, February). Pani and her colleagues (2024) studied the impact of using AI chatbots on autonomy. They found that AI chatbots can serve as an assistive tool by offering suggestions, advice and collaborating with the user to indirectly promote a sense of belonging and lessen feelings of loneliness. With respect to age differences in this relationship, Dong, Xie and Gong (2025) found that the use of AI was not significantly associated with loneliness in younger individuals (aged 35 and below), while in older adults (65 and above), it was positively associated. We also have some evidence to show that loneliness could lead to increased conversational AI use intention. A 2025 study in China found that loneliness significantly enhanced the intention to use conversational AI with parasocial interaction as a mediator and anthropomorphic interface as a moderator (Peng, Zhang, Wen, & Liu, 2025).

### Rationale

Based on this literature review, we framed the main research question for this study: "What is the impact of the widespread use of AI-driven LLMs

on academic self-esteem, loneliness and cognitive flexibility of adolescents?"

While several studies focus on AI's impact on college students, we see a gap in the analysis of school children. The access and use of AI by school-going children are different, and thus, we believe there will be key differences. Cognitive flexibility, the ability to adapt quickly to new situations, develops when critical thinking and metacognition develop, which Piaget tells us is possible for adolescents. Hence, the impact of AI on this variable is also considered significant. As adolescence is a period when social relationships are navigated, and the literature points to a relationship between Loneliness and use of AI, we also believe this will be a significant finding. Finally, the impact of learning outcomes and the method of learning will also impact self-evaluations, and thus, academic self-esteem was chosen as a key outcome variable, keeping in mind the importance of "identity formation" in this life stage.

### Methods

The study uses a cross-sectional survey design, with a mediation analysis to test the above-mentioned research question. The question was broken down into 8 specific hypotheses, mentioned below:

H1: There is a significant positive correlation between the use of AI-driven LLMs and a positive attitude towards AI.

H2: There is a significant positive correlation between the use of AI-driven LLMs and loneliness

H3: The relationship between the use of AI-driven LLMs and loneliness is mediated by a negative attitude towards AI and anxiety about dependence on technology

H4: There is a significant positive correlation between the use of AI-driven LLMs and cognitive flexibility

H5: The relationship between the use of AI-driven LLMs and cognitive flexibility is mediated by preference for task switching

H6: There is a significant positive correlation between the use of AI-driven LLMs and academic self-esteem

H7: The relationship between the use of AI-driven LLMs and academic self-esteem is mediated by cognitive flexibility

H8: There is a significant negative correlation between Academic Self-esteem and loneliness

### Procedure

The study was pre-registered on OSF before data collection (DOI: [10.17605/OSF.IO/H8P23](https://doi.org/10.17605/OSF.IO/H8P23)). All ethical practices prescribed by the University of Andhra were followed after IRB clearance from the department. Informed consent was obtained from the participants. Parents were informed through the school, and those who did not wish their children to participate were not approached for the data collection. Anonymity and confidentiality were maintained. The students were informed of the intention of the study and also debriefed to ensure they had no queries about the use of their data. The data were anonymised and will be stored in a password-protected

computer and can be made available on reasonable request to the corresponding author.

### Sampling

The sample consists of adolescents aged 12 to 19 from various schools in India. The targeted sample size was 384 based on Krejcie and Morgan's (1970) guidelines. Cluster sampling was used as it enhances variability and is less demanding of resources (Iqbal Jeelani et al., 2018). Participants were required to fill out an online survey with the 5 scales (presented in the supplementary materials). Demographic information sought includes age, gender, family income, which class they are in, and whether they have access to the internet.

### Sample

The sample collected has 507 participants, but 100 responses had to be discarded due to failure in the awareness checks, duplication or incomplete responses. Thus, 407 responses were analysed further. The average age of the sample was 12.7 (SD = 1.48), with a maximum of 19 and a minimum of 12 years. The demographic details are presented in Table 1

**Table 1: Sample Characteristics**

| Variable | Categories       | Frequency | Percentage |
|----------|------------------|-----------|------------|
| Gender   | Female           | 188       | 46.2 %     |
|          | Male             | 219       | 53.8 %     |
| SES      | Low              | 6         | 1.50%      |
|          | Middle           | 23        | 5.70%      |
|          | High             | 378       | 92.90%     |
| Class    | Not School-Going | 4         | 1.0 %      |
|          | 6                | 7         | 1.7 %      |
|          | 7                | 11        | 2.7 %      |
|          | 8                | 31        | 7.6 %      |
|          | 9                | 130       | 31.9 %     |

|                    |                                                                              |     |        |
|--------------------|------------------------------------------------------------------------------|-----|--------|
|                    | 10                                                                           | 106 | 26.0 % |
|                    | 11                                                                           | 77  | 18.9 % |
|                    | 12                                                                           | 41  | 10.1 % |
| <hr/>              |                                                                              |     |        |
| Access to Internet | Access to Internet at Home                                                   | 400 | 98.30% |
|                    | No access at home (Have access at school, in houses of relatives or friends) | 7   | 1.70%  |
| <hr/>              |                                                                              |     |        |

### Scales

**AI usage** was measured using the ChatGPT Usage scale, modified to be non-specific to any AI-based LLM. The original scale was developed in 2024 by Nemt-Allah and their colleagues. It consists of 15 items (eg. “I trust the quality and accuracy of AI outputs” (Nemt-Allah, Khalifa, Badawy, Elbably, & Ibrahim, 2024). The response is collected using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The internal consistency is over 0.7, which is considered acceptable (Nunnally & Bernstein, 1994). Exploratory and confirmatory factor analysis were performed, and three sub-dimensions were identified, namely, academic writing aid, academic task support and reliance and trust.

**Attitude towards AI and Technology** use was measured using the attitudes subscale of the Media and Technology Usage and Attitudes Scale (Rosen, Whaling, Carrier, Cheever, & Rokkum, 2013). The scale has 16 items like “I am dependent on my technology” that fall into 4 sub-dimensions – positive attitudes towards technology, anxiety about being without technology, negative attitudes towards technology and preference for task switching. The Cronbach's alpha for these sub-scales ranges from 0.87 to 0.80, which is satisfactory. The scale has been validated against the technology-related anxiety scale and the internet addiction test, and thus has sufficient content and construct validity.

**Academic Self-esteem** was measured by applying the scale used by Tiwari (2011). It was developed for use in the Indian population and was chosen for its brevity. The scale has 7 items

measuring academic self-esteem, like “I succeed at whatever I do at school. The response scale is a 5-point Likert (1 = strongly disagree to 5 = strongly agree). The Cronbach's alpha was 0.85 in the author's original study.

**Cognitive flexibility** was measured using the Cognitive Flexibility Scale (Martin & Rubin, 1995). It is a 12-item scale that is rated on a 6-point Likert scale, ranging from 1 (strongly disagree) to 6 (strongly agree). Zagaria and others (2024) established the psychometric properties; the reliability was computed to be 0.834, and factor analysis was also performed.

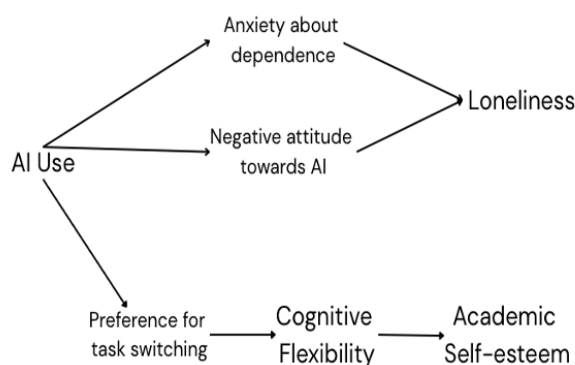
**Loneliness** was measured using one subscale of the HILDA (Household, Income, Labour and Dynamics in Australia) survey. This scale has 10 items that measure loneliness and social isolation. Reliability was established to be 0.7 and 0.8, respectively, for these domains (Manera, Smith, Owen, Phongsavan, & Lim, 2022). The factor structure was validated using confirmatory factor analysis. A sample item is “I often need help from other people but can't get it.” The response is collected on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

### Analysis

The data were cleaned to remove duplicate and patterned responses. The descriptives were calculated, and the reliability of the tools was established. Pearson correlation was performed. Mediation analysis was performed for the relevant relationships using GLM to correct for errors caused by repeated testing. The overall model to be tested is depicted in Figure 1. The analysis was performed on Jamovi, an open-

source R-based software (The Jamovi Project, 2023; R Core Team, 2022; Revelle, 2023; Gallucci, 2020).

**Figure 1 Relationships hypothesised in this study**



## Results

The average scores of all the variables of interest are presented in Table 2.

**Table 2** Descriptive statistics for all variables

|                               | N   | Mean  | SD     | Maximum score | Minimum score |
|-------------------------------|-----|-------|--------|---------------|---------------|
| Loneliness Total              | 407 | 30.88 | 12.257 | 63            | 9             |
| Cognitive Flexibility total   | 407 | 58.24 | 8.931  | 84            | 12            |
| Academic Self-Esteem total    | 407 | 25.51 | 4.517  | 35            | 7             |
| Preference for task switching | 407 | 3.88  | 0.939  | 20            | 4             |
| Negative Attitude             | 407 | 9.34  | 2.315  | 18            | 3             |
| Anxiety about dependence      | 407 | 8.05  | 2.587  | 18            | 3             |
| Positive Attitude             | 407 | 20.97 | 3.701  | 30            | 6             |
| AI Use Total                  | 407 | 53.42 | 7.387  | 75            | 15            |

Before further analysis, the reliability of the tools used for this sample was ascertained by the calculation of Cronbach's alpha. Levels between 0.70 and 0.95 are generally considered acceptable (Tavakol & Dennick, 2011), and all of the scales fall within this range except Attitude towards AI. The same paper says that lower scores could be

because of heterogeneity of the construct, and we believe that since this scale has two positive and two negative sub-dimensions, one of them (preference for task switching) is quite different from the others. Thus, the lower value can be explained. Based on this, we decided to go ahead with the analysis using this scale.



**Table 3: Reliability Statistics**

| Scale                 | No. of Items | Crohnbach Alpha |
|-----------------------|--------------|-----------------|
| AI Use                | 15           | 0.794           |
| Attitude towards AI   | 16           | 0.658           |
| Cognitive Flexibility | 12           | 0.742           |
| Academic Self-esteem  | 7            | 0.801           |
| Loneliness            | 10           | 0.842           |

Table 4 shows the Pearson correlation for the variables of interest. As the sample size was large (N=407), normality was assumed (Altman & Bland, 1995).

**Table 4: Pearson Correlation for variables of interest**

|             | Academic |          |            |           |            |          |             |            |
|-------------|----------|----------|------------|-----------|------------|----------|-------------|------------|
|             | AI Use   | Positive | Anxiety    | Negative  | Preference | Self-    | Cognitive   | Loneliness |
|             | Total    | Attitude | about      | Attitude  | for        | task     | Flexibility | Total      |
|             |          |          | dependence | switching | total      | total    |             |            |
| AI Use      | —        |          |            |           |            |          |             |            |
| Positive    |          | —        |            |           |            |          |             |            |
| Attitude    | 0.229*** |          |            |           |            |          |             |            |
| Anxiety     |          |          | —          |           |            |          |             |            |
| about       |          |          |            | —         |            |          |             |            |
| dependence  | 0.169*** | 0.241*** |            |           |            |          |             |            |
| Negative    |          |          |            | —         |            |          |             |            |
| Attitude    | -0.162** | -0.115*  | -0.06      |           |            |          |             |            |
| Preference  |          |          |            |           | —          |          |             |            |
| for task    |          |          |            | 0.097     |            |          |             |            |
| switching   | -0.008   | -0.007   | -0.097     |           |            |          |             |            |
| Academic    |          |          |            |           |            | —        |             |            |
| Self-       |          |          |            |           |            |          |             |            |
| Esteem      |          |          |            |           |            |          |             |            |
| total       | 0.021    | -0.014   | -0.054     | -0.02     | 0.097      |          |             |            |
| Cognitive   |          |          |            |           |            |          | —           |            |
| Flexibility |          |          |            |           |            |          |             |            |
| total       | 0.1*     | 0.144**  | -0.239***  | -0.04     | 0.107*     | 0.478*** |             |            |

## Loneliness

|       |       |        |         |       |      |          |           |   |
|-------|-------|--------|---------|-------|------|----------|-----------|---|
| Total | 0.025 | -0.074 | 0.159** | 0.045 | 0.01 | -0.33*** | -0.436*** | — |
|-------|-------|--------|---------|-------|------|----------|-----------|---|

Note: \* indicates significance at 0.05 level, \*\* at 0.01 level and \*\*\* at 0.001 level

AI use was positively correlated with positive attitude ( $r = .23$ ,  $p < .001$ ), anxiety about dependence ( $r = .17$ ,  $p < .001$ ), and cognitive flexibility ( $r = .10$ ,  $p < .05$ ). It was negatively correlated with negative attitude ( $r = -.16$ ,  $p < .01$ ). Positive attitude was positively associated with anxiety about dependence ( $r = .24$ ,  $p < .001$ ) and cognitive flexibility ( $r = .14$ ,  $p < .01$ ). Negative attitude showed a negative correlation with positive attitude ( $r = -.12$ ,  $p < .05$ ). Cognitive flexibility was positively correlated with academic self-esteem ( $r = .48$ ,  $p < .001$ ) and negatively correlated with anxiety about dependence ( $r = -.24$ ,  $p < .001$ ) and loneliness ( $r = -.44$ ,  $p < .001$ ). Academic self-esteem was negatively correlated with loneliness ( $r = -.33$ ,  $p < .001$ ). Finally, anxiety about dependence was positively correlated with loneliness ( $r = .16$ ,  $p < .05$ ). Based

on this, Hypotheses 1, 3 and 5 were supported, and 2 and 4 were not supported by the data.

As not all the correlations were significant, the hypothesised mediation model could not be tested. Hence, two separate models were tested. The first examines the role of Positive attitude towards technology as a mediator between AI Use (independent variable) and Cognitive Flexibility (Dependent variable), depicted in Figure 2 and Table 5. The second model examined the mediation of academic self-esteem between Cognitive Flexibility (Independent) and Loneliness (Dependent variable), depicted in Table 6 and Figure 3. We also tested the regression of anxiety about dependence on loneliness, as the correlation was significant; the results of which are in Table 7.

**Table 5: Mediation of Academic Self-esteem between Cognitive Flexibility and Loneliness**

| Mediation Estimates                       |          |        |      |        |
|-------------------------------------------|----------|--------|------|--------|
| Effect                                    | Estimate | SE     | Z    | p      |
| Indirect                                  | 0.0261   | 0.0106 | 2.46 | 0.014  |
| Direct                                    | 0.0566   | 0.0402 | 1.41 | 0.159  |
| Total                                     | 0.0827   | 0.0408 | 2.03 | 0.043  |
| Path Estimates                            |          |        |      |        |
| Path                                      | Estimate | SE     | Z    | p      |
| Cognitive Flexibility → Positive Attitude | 0.0595   | 0.0203 | 2.93 | 0.003  |
| Positive Attitude → AI Use                | 0.4378   | 0.0971 | 4.51 | < .001 |
| Cognitive Flexibility → AI Use            | 0.0566   | 0.0402 | 1.41 | 0.159  |

The results indicate that there is full mediation of positive attitude between AI use and cognitive flexibility, as the total and path estimates are significant and the direct effect is not significant.

**Table 6 : Mediation of Academic Self-Esteem between Cognitive Flexibility and Loneliness**

| Mediation Estimates                          | Estimate | SE     | Z     | p      |
|----------------------------------------------|----------|--------|-------|--------|
| Indirect                                     | -0.104   | 0.0342 | -3.03 | 0.002  |
| Direct                                       | -0.494   | 0.0688 | -7.18 | < .001 |
| Total                                        | -0.598   | 0.0612 | -9.77 | < .001 |
| Path Estimates                               | Estimate | SE     | Z     | p      |
| Cognitive Flexibility → Academic Self-Esteem | 0.242    | 0.022  | 10.97 | < .001 |
| Academic Self-Esteem → Loneliness            | -0.43    | 0.1361 | -3.16 | 0.002  |
| Cognitive Flexibility → Loneliness           | -0.494   | 0.0688 | -7.18 | < .001 |

These results indicate that academic self-esteem is a partial mediator between cognitive flexibility and loneliness.

**Table 7: Regression of Anxiety about Dependence on Loneliness**

|                          | R <sup>2</sup> | Estimate | SE    | t     | p      |
|--------------------------|----------------|----------|-------|-------|--------|
| Intercept                | 0.0253         | 24.82    | 1.966 | 12.62 | < .001 |
| Anxiety about dependence |                | 0.753    | 0.232 | 3.24  | 0.001  |

The regression of Anxiety about dependence on Loneliness was found to be small (2.53%) but significant at the 0.001 level.

## Discussion

Adolescence is a period when self and social identity are still developing. Cognitive capabilities develop during this period, while neural connections are rapidly formed and pruned. In this period, the introduction of technology has had certain impacts. This study examined the use of AI-based LLMs, attitude towards this technology and its impact on three key outcome variables - (i) Cognitive flexibility - the ability to adapt to new tasks and apply learning in a

different context (Bream & Egner, 2018), (ii) Academic Self-esteem - evaluation of the self in the academic setting and (iii) Loneliness - the feeling of social isolation.

The connection between AI use and “Attitude towards AI” was a key finding in this study. We believe that the beliefs about AI - its use, its negative impact, and worry about dependence - influence the behaviour of actually using AI-based LLMs. We found that AI use was positively correlated with positive attitude and

negatively correlated with negative attitude. Interestingly, anxiety about dependence was also positively associated with both AI use and positive attitude. On one hand, adolescents have positive beliefs about the transformative potential of AI. But on the other they are aware that their behaviour may lead to dependence on such tools, leading to anxiety when they don't have access.

We believe that more studies should look at the motivations behind using AI across different age groups. There is literature showing loneliness could influence the intention to use conversational AI tools (Peng et al., 2025). While there are studies that look at AI as an intervention for loneliness, we have evidence that it does not replace social relationships (Patulny and Bower, 2022). Given that LLMs and AI technology now constitute an integral part of the contemporary world, it is crucial to consider not only their observable use, but also the social, cognitive and deeply psychological factors that shape the patterns of use.

Most studies, whether in psychology, education, or information systems, consider AI tools as “Janus-faced” (Susarla, 2023; Netzer, 2024; Zhan et al., 2024). Studies reveal divergent conclusions about how LLMs influence cognitive processes. Scholars asserted that critical executive functions like writing were lost (Dubey et al., 2024), and these tools lowered recall (Kosmyna et al., 2025). Other studies said that it could stimulate creativity (Lin and Chen, 2024) and critical thinking (Melisa et al., 2025). We chose the outcome cognitive flexibility as it refers not only to quickly switching between tasks but also to the ability to apply knowledge outside the context in which it was learned and use theoretical knowledge to solve problems.

In our study, cognitive flexibility was positively associated with AI use, showing that adaptability to different situations is enhanced. It was also positively correlated with academic self-esteem and negatively correlated with anxiety about dependence. Hence, adolescents who were able to adapt and apply their knowledge were less worried about becoming chronically dependent on LLMs. Presumably, they were able to learn from it and

believed they could manage without these tools in the future. Future studies can examine these beliefs and also examine the way students use LLMs in a school setting. In most Indian schools, computers are not available in class and so can be used only for homework or studies before exams, as opposed to university settings where note-taking on tablets and laptops is permitted, which gives ready access to LLMs even during classes.

We find that a positive attitude is a full mediator between AI use and cognitive flexibility. This suggests that people's beliefs about AI significantly shape how it affects cognitive outcomes. In other words, the impact of AI is not fixed, and it depends on attitudes and expectations, which influence the way individuals engage with systems – connecting to Bandura's theory of reciprocal determinism (1978) and, in the field of information systems, the Technology Acceptance Model (Davis, 1989). We believe this is a gap in the research that should be addressed. Intention and knowledge drive behaviour. Thus, AI use behaviour will be contingent on beliefs about the technology and one's own ability to use it without overdependence. AI literacy is also important, as highlighted by several studies.

Academic self-esteem was positively correlated with cognitive flexibility and negatively correlated with loneliness. The mediation model showed a partial mediator. Academic self-esteem is only a part of the self-concept of the adolescent, and thus other aspects of the self will certainly influence loneliness as an outcome. Cognitive flexibility impacts academic self-esteem as noted in the path-estimates (.242,  $p < 0.001$ ). When considering holistic models of education, it is important to take information from the academic context and apply it outside the classroom. If this model is reinforced, then this pathway can be strengthened.

Finally, loneliness was positively correlated with anxiety about dependence. This shows that perhaps children use technology for coping with loneliness and are aware of their disengagement from their peers. While no causal relationship is

tested in this study, the positive correlation shows scope for future investigation. This study particularly focuses on how social buffers may allow safe exploration of AI-driven technology during adolescence. While the correlation itself was quite weak, its significance at the 0.01 level indicates that this relationship is statistically reliable and thus can be investigated more qualitatively for more insights.

While AI has been used to alleviate loneliness in some cases, the organic use of AI in individuals, particularly adolescents, could lead to both positive outcomes, like better coping, but also negative effects, like withdrawal and social pruning (Patulny and Bower, 2022). Studies have shown differences across age groups (Landmann and Rohmann, 2022). Even in the learning context, Gen Alpha, who were born into the AI era, are likely to use technology in a different way than Millennials or Generation Z, who may be in universities/college. Hence, these differences also need to be considered in future studies.

### **Limitations**

The study takes a cross-sectional and quantitative approach, limiting an in-depth understanding of AI use and its impact. Interviews from an interpretivist paradigm focusing on the co-creation of Human-AI interactions can yield rich responses. AI has been part of everyday life for some time now, and longitudinal studies can give a clearer picture of the positive and negative impact, based on which policy decisions can be made.

### **Implications**

This study attempts to provide a novel insight into the behavioural patterns associated with the use of LLMs. Taken together, the findings point to a critical need for future work to investigate, with greater precision, how users' beliefs about AI shape their behaviour and engagement with the technology. Existing studies focus on cognitive impact after specific cognitive tasks and academic outcomes; however, taking a more holistic view of

how AI has changed the way people learn and relate with people is needed, and this study offers some insight into how these variables are related. Practical implications for educators are to consider the access to technology that students have and develop activities and assessments that make them think out of the box. Group activities to foster social learning and reduce isolation within and outside the classroom can be considered. For parents, rather than limiting access, enhancing AI literacy can ensure their children use technology productively as a tool, rather than a crutch. The use of AI also comes with ethical and moral questions, and researchers and educators need to consider these dilemmas and not leave it to adolescents, whose anxiety about dependence may not be enough to limit their use (or abuse) of such technology.

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The authors acknowledge no competing interests.

### **Data Availability Statement**

The data collected in this study are not published online in any repository; this is due to the ethical policy of Andhra University. However, they can be made available upon reasonable request addressed to the corresponding author.

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### **Data Availability Statement**

The data associated with this study will be made available on reasonable request by contacting the corresponding author.

### **Conflict of Interest**

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