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Does depression drive technology overuse or vice-versa? a cross-lagged panel analysis of bidirectional relationships among Chinese university students

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Abstract

Background The escalating prevalence of depression among university students coincides with unprecedented technology engagement, yet the directional relationship remains contested. While cross-sectional research suggests associations between technology use patterns and depressive symptoms, longitudinal evidence examining bidirectional influences remains scarce, particularly in non-Western populations.

Objective This study aimed to examine the bidirectional relationships between specific technology use patterns and depression severity among Chinese university students using a methodologically rigorous longitudinal design.

Methods This study conducted a four-wave longitudinal study with assessments at 3-month intervals among undergraduate students ($N = 737$) from three universities in eastern China. Participants completed validated measures of depression (Patient Health Questionnaire-9), anxiety (Generalized Anxiety Disorder-7), and technology use patterns (duration, timing, motivational contexts). Cross-lagged panel models with random intercepts were used to examine bidirectional relationships while controlling for between-person differences and covariates.

Results Total technology use exhibited significant bidirectional relationships with depression, but specific patterns showed distinct relationships. Night-time use ($\beta = 0.16$, 95% CI [0.08–0.24], $p < 0.001$) and social-comparison-motivated use ($\beta = 0.19$, 95% CI [0.11–0.27], $p < 0.001$) predicted subsequent increases in depression, with stronger effects than the reverse pathway (depression to increased technology use). Conversely, depression predicted increased escapism-motivated technology use ($\beta = 0.23$, 95% CI [0.14–0.32], $p < 0.001$) more strongly than the reverse pathway. Body mass index significantly moderated these relationships, with stronger technology-to-depression effects among participants with overweight/obesity ($\beta = 0.27$, 95% CI [0.16–0.38], $p < 0.001$) compared to normal-weight participants ($\beta = 0.11$, 95% CI [0.03–0.19], $p = 0.009$). The observed relationships remained significant after adjusting for anxiety, sleep quality, and socioeconomic factors.

Conclusion These findings reveal complex, pattern-specific bidirectional relationships between technology use and depression, with important temporal precedence differences. The results suggest that certain technology use contexts may contribute more strongly to depression development, while depression may drive other specific

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usage patterns. These findings have implications for targeted intervention approaches addressing both depression and problematic technology use among university students.

Keywords Depression, Digital technology, University students, Longitudinal study, Cross-lagged panel model, Bidirectional relationship, China

Introduction

Depression represents a leading cause of disability worldwide, with university students demonstrating particularly elevated vulnerability [28]. Recent epidemiological studies indicate concerning prevalence rates among university students in China, ranging from 23.8% to 40.1% [2, 16]. This mental health crisis has emerged alongside dramatic increases in digital technology engagement, with the average Chinese university student now spending approximately 8 h daily on internet-connected devices [29]. The temporal co-occurrence of rising depression rates and increased technology engagement has spurred substantial research interest in their potential causal relationships. Cross-sectional studies have consistently demonstrated associations between technology use and depression symptoms [6, 12, 18]. However, the directional nature of this relationship remains contested, with competing theoretical frameworks suggesting three possible pathways: technology use contributing to depression ("digital displacement hypothesis"), depression driving increased technology use ("compensatory internet use theory"), or bidirectional relationships [13, 24]. The digital displacement hypothesis posits that excessive technology use displaces health-promoting activities like face-to-face social interaction, physical activity, and adequate sleep, thereby increasing depression vulnerability [20]. Meanwhile, compensatory internet use theory suggests that individuals experiencing depression symptoms may increase technology engagement to alleviate negative affect, escape distressing thoughts, or compensate for perceived real-world deficits [13]. Additionally, the differential susceptibility to media effects framework [24] proposes that media effects are not universal but conditional, depending on dispositional, developmental, and social susceptibility factors. This framework suggests that certain individuals, based on pre-existing vulnerabilities or characteristics (such as BMI status), may be more susceptible to potential negative effects of specific technology use patterns. These competing frameworks have different implications for intervention approaches.

Recent methodological advances have emphasized the importance of distinguishing between-person from within-person effects in longitudinal studies [9]. Traditional cross-lagged panel models may conflate these effects, potentially yielding misleading conclusions about temporal precedence. Additionally, growing evidence suggests that examining technology use as a monolithic construct obscures important pattern-specific relationships with depression [21, 25]. Specific dimensions including timing (e.g., night-time use), motivational context (e.g., social comparison, escapism), and psychological experience (e.g., problematic use, fear of missing out) may have distinct relationships with depression trajectories. While several longitudinal studies have begun examining bidirectional technology-depression relationships in Western populations [5, 10, 23], important knowledge gaps remain. First, most studies have not employed methodologically rigorous approaches that separate between-person from within-person effects. Second, research examining pattern-specific bidirectional relationships remains scarce. Third, potential moderating factors that may influence technology-depression relationships, such as body mass index (BMI), have received limited attention despite theoretical relevance. Finally, research in non-Western contexts, particularly China, which has both high rates of technology engagement and unique cultural factors influencing depression expression, remains limited. To address these gaps, this study conducted a four-wave longitudinal study examining bidirectional relationships between specific technology use patterns and depression among Chinese university students. The study employed random-intercept cross-lagged panel models (RI-CLPM) to distinguish between-person from within-person effects, while examining multiple technology use dimensions and potential moderating factors. Our primary hypotheses were:

1. Technology use patterns and depression symptoms would demonstrate significant bidirectional relationships at the within-person level.
2. The strength and direction of relationships would vary across specific technology use patterns, with night-time use and social-comparison-motivated use showing stronger technology-to-depression effects, and escapism-motivated use showing stronger depression-to-technology effects.
3. The observed relationships would be moderated by BMI, with stronger associations among participants with overweight/obesity.

Methods

Study design and participants

This four-wave longitudinal study collected data at 3-month intervals between October 2023 and October 2024. The study recruited undergraduate students from three universities in eastern China and all participants provided electronic informed consent. Eligible participants were: (1) full-time undergraduate students, (2) aged 18–24 years, (3) Chinese nationals, and (4) owners of smartphones with internet access. Exclusion criteria included: (1) current diagnosis of severe mental illness, (2) pregnancy or breastfeeding, (3) history of substance use disorder, (4) serious physical illness or personality disorder, and (5) inability to complete psychological evaluations. Based on our planned analyses, the study determined that a sample size of 720 participants would provide 90% power to detect small-to-medium effects ($\beta = 0.15$) at $\alpha = 0.05$, accounting for anticipated attrition of 20% across waves. The study initially recruited 848 participants, 737 of whom completed baseline assessments and were included in the study.

Measures

Depression and anxiety symptoms

Depression was measured using the Patient Health Questionnaire-9 (PHQ-9) [14], a 9-item self-report measure assessing DSM-IV depression criteria on a 4-point scale (0 =not at all to 3= nearly every day), yielding total scores from 0–27. The Chinese version has demonstrated good psychometric properties (Cronbach's $\alpha = 0.86–0.89$) [27]. Anxiety was measured using the 7-item Generalized Anxiety Disorder scale (GAD-7) [22], with scores ranging from 0–21 (Cronbach's $\alpha = 0.88$ in this sample).

Technology use patterns

Technology use was assessed with the Technology Use Questionnaire (TUQ), developed based on previous research and validated in Chinese populations [3, 17]. The TUQ measures multiple dimensions:

1. Daily usage duration: Total hours of technology use across devices, categorized as essential (academic/professional) and non-essential (recreational).
2. Timing of use: Frequency of morning, afternoon, evening, and night-time (after intended bedtime) use on a 5-point scale (1 =never to 5= always). Night-time use was specifically defined as technology use occurring after the participant's self-reported intended bedtime. Participants reported their typical intended bedtime at each assessment wave, and night-time use was measured relative to this individualized reference point rather than a standardized time. This approach accounts for the variability in university students' sleep schedules.
3. Motivational contexts: Frequency of technology use for specific motivations, including:
   - Social connection (e.g., to maintain relationships)
   - Information seeking (e.g., to find information or learn)
   - Entertainment (e.g., to relieve boredom)
   - Social comparison (e.g., to see how others' lives compare to mine)
   - Escapism (e.g., to avoid thinking about problems)
4. Problematic use: Measured using the Chinese version of the Smartphone Addiction Scale-Short Version (SAS-SV) [15], a 10-item scale assessing symptoms of problematic smartphone use (Cronbach's $\alpha = 0.88$ in this sample).

Anthropometric and health measures

Height and weight were measured by trained research assistants using standardized protocols. BMI was calculated (kg/m^2) and categorized according to Chinese obesity classification standards: underweight (< 18.5), normal weight (18.5–23.9), overweight (24.0–27.9), and obese (≥ 28.0) [31]. Sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI) [1].

Sociodemographic and academic variables

Participants reported age, gender, family monthly income, personal monthly income, residential arrangement, academic year, and academic performance (previous semester GPA).

Procedure

Participants were recruited through campus advertisements, course announcements, and student organization networks. Interested students completed eligibility screening online. Eligible participants attended an in-person baseline session where they provided informed consent, completed anthropometric measurements, and accessed a secure online platform to complete questionnaires. Subsequent assessments at 3, 6, and 9 months were conducted online, with email and text message reminders sent 3 days before and on the scheduled assessment day. Participants received ¥50 for the baseline assessment and ¥30 for each follow-up, with an additional ¥50 bonus for completing all assessments.

Statistical analysis

The study used random-intercept cross-lagged panel models (RI-CLPM) to examine bidirectional relationships between technology use patterns and depression while controlling for between-person effects [9]. The RI-CLPM decomposes the variance in observed scores into stable between-person differences (random intercepts) and within-person fluctuations over time. Cross-lagged paths between within-person components represent the extent to which deviations from a person's expected score on one variable predict subsequent deviations in the other variable. Models were estimated using maximum likelihood with robust standard errors (MLR) in Mplus version 8.4. Prior to conducting the main analyses, we tested longitudinal measurement invariance for our key measures across the four assessment waves. Following standard procedures, we sequentially evaluated configural invariance (same factor structure across time), metric invariance (equal factor loadings across time), and scalar invariance (equal intercepts across time). Results supported adequate measurement invariance for all measures, indicating that observed changes over time reflect true changes rather than measurement artifacts. Model fit was evaluated using comparative fit index (CFI; >0.95 indicating good fit), Tucker-Lewis index (TLI; >0.95), root mean square error of approximation (RMSEA; <0.06), and standardized root mean square residual (SRMR; <0.08) [11]. The study first examined a series of bivariate RI-CLPMs between depression and each technology use dimension. Subsequently, we tested multivariate models controlling for anxiety, sleep quality, and sociodemographic factors. To examine potential moderation by BMI, we conducted multi-group RI-CLPMs comparing normal weight versus overweight/obese participants. Missing data were handled using full information maximum likelihood estimation. To address potential selection bias due to attrition, we conducted pattern-mixture models comparing different missing data patterns [7].

Results

Sample characteristics and attrition

Of the 737 participants who completed baseline assessments, 684 (92.8%) completed the 3-month follow-up, 651 (88.3%) the 6-month follow-up, and 627 (85.1%) the 9-month follow-up. Table 1 presents baseline characteristics of the sample. Mean age was 20.3 years (SD =1.7), with 66.2% female participants. Approximately 55.6% of participants were classified as overweight or obese. At baseline, 33.2% reported moderate-to-severe depression symptoms (PHQ-9 ≥10). Participants reported an average of 7.8 h (SD =2.6) daily technology use. Participants

Table 1 Baseline characteristics of study participants (*N* = 737)

Characteristic	Value
Demographics	
Age, mean (SD), years	20.3 (1.7)
Gender, *n* (%)	
Female	488 (66.2)
Male	249 (33.8)
Academic year, *n* (%)	
First year	243 (33.0)
Second year	258 (35.0)
Third year	189 (25.6)
Fourth year	47 (6.4)
Monthly family income (CNY), *n* (%)	
< 3000	118 (16.0)
3000–6000	276 (37.4)
6001–10000	224 (30.4)
> 10,000	119 (16.1)
Residential arrangement, *n* (%)	
University dormitory	619 (84.0)
Off-campus housing	93 (12.6)
With family	25 (3.4)
Clinical Measures	
BMI, mean (SD), kg/m^2	24.1 (3.9)
BMI category, *n* (%)	
Underweight (< 18.5)	70 (9.5)
Normal weight (18.5–23.9)	257 (34.9)
Overweight (24.0–27.9)	304 (41.2)
Obese (≥ 28.0)	106 (14.4)
PHQ-9 score, mean (SD)	7.9 (5.3)
Depression severity, *n* (%)	
Minimal (0–4)	261 (35.4)
Mild (5–9)	231 (31.3)
Moderate (10–14)	157 (21.3)
Moderately severe (15–19)	69 (9.4)
Severe (≥ 20)	19 (2.6)
GAD-7 score, mean (SD)	6.3 (4.7)
Technology Use	
Total daily usage, mean (SD), hours	7.8 (2.6)
Essential usage, mean (SD), hours	3.1 (1.8)
Non-essential usage, mean (SD), hours	4.7 (2.2)
Night-time use (after intended bedtime), *n* (%)	
Never/rarely	109 (14.8)
Sometimes	231 (31.3)
Often/always	397 (53.9)
Social-comparison-motivated use, mean (SD)*	3.1 (1.1)
Escapism-motivated use, mean (SD)*	3.4 (1.0)
Problematic use (SAS-SV), mean (SD)	32.6 (9.7)

* Measured on a 5-point scale (1 = never to 5 = always)

who completed all assessments did not differ significantly from those with missing data on baseline depression, technology use, or demographic characteristics, suggesting limited potential for selection bias due to attrition.

Longitudinal trends

Table 2 presents means and standard deviations for key variables across all assessment waves. Depression symptoms showed modest fluctuations over time, with slight decreases from baseline ($M = 7.9$, $SD = 5.3$) to the final assessment ($M = 7.3$, $SD = 4.9$). Total technology use remained relatively stable, but specific patterns showed different trajectories. Night-time use increased slightly over time, while social-comparison-motivated use decreased slightly. Within-person correlation analysis revealed significant contemporaneous associations between depression and technology use dimensions at each wave, with the strongest correlations for escapism-motivated use ($r = 0.31–0.38$) and night-time use ($r = 0.27–0.34$).

Bidirectional relationships between depression and technology use

Total technology use

The bivariate RI-CLPM examining reciprocal relationships between total technology use and depression demonstrated good fit (CFI =0.982, TLI =0.970, RMSEA =0.038, SRMR =0.035). Both cross-lagged paths were statistically significant, indicating bidirectional relationships (Fig. 1). Technology use predicted subsequent increases in depression (standardized $\beta = 0.14$, 95% CI [0.06–0.22], $p = 0.001$), and depression predicted subsequent increases in technology use (standardized $\beta = 0.11$, 95% CI [0.03–0.19], $p = 0.008$). These effects remained significant after controlling for anxiety, sleep quality, and sociodemographic factors in multivariate models.

Pattern-specific analyses

Separate RI-CLPMs were estimated for each technology use pattern. All models demonstrated good fit (CFI =0.954–0.989, RMSEA =0.031–0.042). Figure 2 presents standardized cross-lagged path coefficients for each technology use dimension. The results revealed pattern-specific differences in the strength and direction of relationships.

Night-time use showed stronger technology-to-depression effects ($\beta = 0.16$, 95% CI [0.08–0.24], $p < 0.001$) than depression-to-technology effects ($\beta = 0.09$, 95% CI [0.01–0.17], $p = 0.025$). Similarly, social-comparison-motivated use demonstrated stronger technology-to-depression effects ($\beta = 0.19$, 95% CI [0.11–0.27], $p < 0.001$) than depression-to-technology effects ($\beta = 0.07$, 95% CI [−0.01–0.15], $p = 0.089$). Conversely, escapism-motivated use showed stronger depression-to-technology effects ($\beta = 0.23$, 95% CI [0.14–0.32], $p < 0.001$) than technology-to-depression effects ($\beta = 0.10$, 95% CI [0.02–0.18], $p = 0.017$), consistent with our hypothesis that depression would more strongly predict escapism-motivated technology use. Problematic use exhibited significant bidirectional relationships with depression, with comparable effect sizes in both directions (technology-to-depression: $\beta = 0.15$, 95% CI [0.07–0.23], $p < 0.001$; depression-to-technology: $\beta = 0.17$, 95% CI [0.09–0.25], $p < 0.001$). Essential technology use (for academic/professional purposes) showed non-significant cross-lagged relationships with depression in both directions ($p > 0.05$), suggesting that academic/professional technology use neither predicted nor was predicted by depression symptoms.

Moderation by BMI

Multi-group RI-CLPMs revealed significant moderation by BMI for several technology use patterns. For night-time use, the technology-to-depression effect was significantly stronger among participants with overweight/obesity ($\beta = 0.27$, 95% CI [0.16–0.38], $p < 0.001$) compared to normal-weight participants ($\beta = 0.11$, 95% CI [0.03–0.19], $p = 0.009$), with a significant difference between groups ($\Delta\beta = 0.16$, $p = 0.014$). Similar moderation patterns were observed for social-comparison-motivated use, with stronger

Table 2 Descriptive statistics for key variables across all assessment waves

Variable	Baseline (T0)	3 Months (T1)	6 Months (T2)	9 Months (T3)
PHQ-9	7.9 (5.3)	7.7 (5.1)	7.5 (5.2)	7.3 (4.9)
GAD-7	6.3 (4.7)	6.1 (4.6)	6.0 (4.5)	5.8 (4.4)
Total technology use (hours/day)	7.8 (2.6)	7.9 (2.7)	7.7 (2.5)	7.8 (2.6)
Night-time use*	3.5 (1.2)	3.6 (1.1)	3.7 (1.2)	3.8 (1.1)
Social-comparison-motivated use*	3.1 (1.1)	3.0 (1.1)	2.9 (1.2)	2.8 (1.1)
Escapism-motivated use*	3.4 (1.0)	3.4 (1.1)	3.5 (1.0)	3.5 (1.1)
Problematic use (SAS-SV)	32.6 (9.7)	32.4 (9.8)	32.7 (10.1)	33.1 (10.0)

* Measured on a 5-point scale (1 = never to 5 = always) Values are presented as mean (standard deviation)

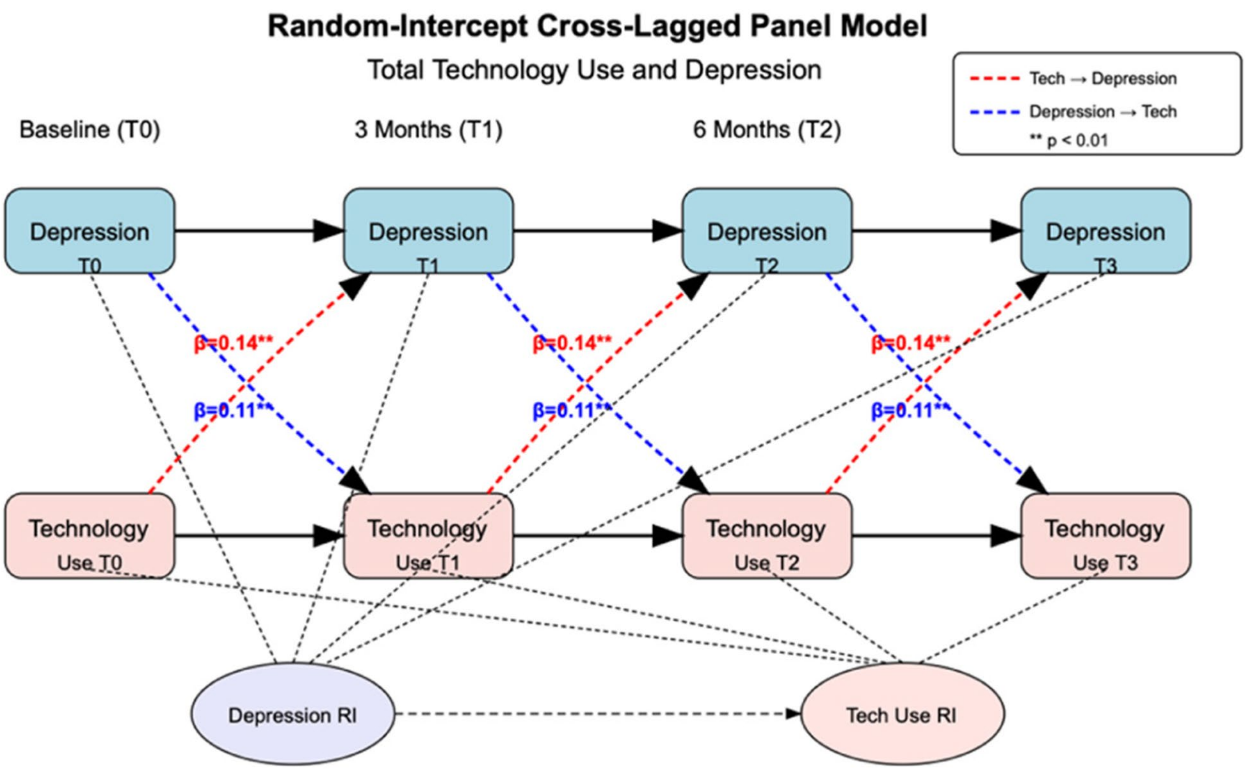

Fig. 1 Random-intercept cross-lagged panel model showing bidirectional relationships between total technology use and depression. This figure presents standardized path coefficients from a random-intercept cross-lagged panel model examining reciprocal relationships between total daily technology use and depression symptoms across four measurement waves. Solid arrows represent statistically significant paths (p <.05). Cross-lagged paths demonstrate significant bidirectional relationships (technology use to depression: $\beta = 0.14$, 95% CI [0.06–0.22], $p = 0.001$; depression to technology use: $\beta = 0.11$, 95% CI [0.03–0.19], $p = 0.008$). Model fit indices indicate excellent fit (CFI = 0.982, TLI = 0.970, RMSEA = 0.038, SRMR = 0.035)

technology-to-depression effects in the overweight/obese group. However, BMI did not significantly moderate the depression-to-technology effects for any use pattern, suggesting that BMI primarily influences how technology use affects depression rather than how depression affects technology use.

Sensitivity analyses

The study conducted several sensitivity analyses to assess the robustness of our findings. First, we estimated models with different missing data handling approaches, which yielded consistent results. Second, the study examined alternative time lags (2-wave and 3-wave intervals), which showed similar but attenuated patterns. Third, the study tested models controlling for baseline academic performance, which did not substantively change the results. Finally, the study conducted gender-stratified analyses, which revealed generally consistent patterns across gender, with slightly stronger technology-to-depression effects among females.

Discussion

This four-wave longitudinal study examined bidirectional relationships between technology use patterns and depression among Chinese university students using methodologically rigorous analyses that distinguished between- from within-person effects. The study findings revealed complex, pattern-specific relationships that advance understanding of how technology use and depression may influence each other over time. Consistent with the study first hypothesis, we found significant bidirectional relationships between total technology use and depression at the within-person level, suggesting reciprocal influences over time. These findings align with the growing body of evidence supporting both the digital displacement hypothesis and compensatory internet use theory [13, 20], indicating that neither theoretical framework is sufficient alone to explain technology-depression relationships. Moreover, our findings provide empirical support for the differential susceptibility to media effects framework [24], as evidenced by the significant BMI moderation effects. This framework proposes that media effects are conditional upon individual susceptibility

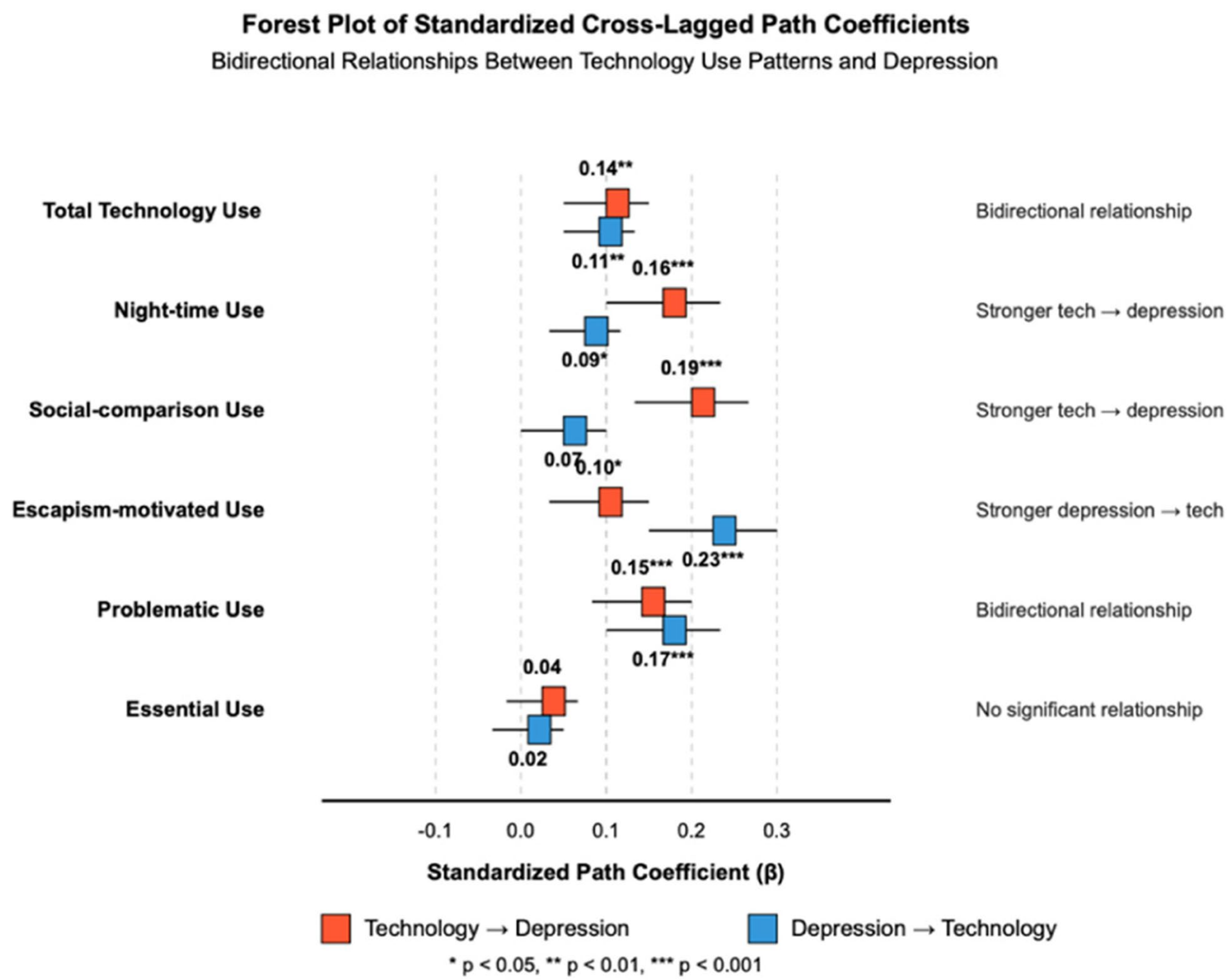

Fig. 2 Forest plot showing standardized cross-lagged path coefficients with 95% confidence intervals for each technology use pattern. This forest plot illustrates standardized path coefficients (β) with 95% confidence intervals for bidirectional relationships between specific technology use patterns and depression. Solid circles represent technology-to-depression effects and hollow circles represent depression-to-technology effects. Night-time use ($\beta = 0.16$, 95% CI [0.08–0.24], $p < 0.001$) and social-comparison-motivated use ($\beta = 0.19$, 95% CI [0.11–0.27], $p < 0.001$) demonstrate stronger technology-to-depression effects, whereas escapism-motivated use exhibits stronger depression-to-technology effects ($\beta = 0.23$, 95% CI [0.14–0.32], $p < 0.001$). Confidence intervals not crossing zero indicate statistical significance ($p < .05$)

factors, which in our study is represented by BMI status. The stronger technology-to-depression effects among participants with overweight/obesity suggest that physical health status may function as a susceptibility factor that amplifies vulnerability to potentially negative effects of certain technology use patterns. This aligns with the framework's proposition that media effects are not universal but rather contingent upon dispositional, developmental, and social susceptibility factors that moderate the direction and strength of effects. Supporting second hypothesis, the study observed pattern-specific variations in the strength and direction of relationships. Night-time use and social-comparison-motivated use showed stronger technology-to-depression effects, consistent with research highlighting the deleterious effects of technology-induced sleep disruption [4] and social comparison processes [26] on mental health. These patterns appear to more strongly drive subsequent depression symptoms than being driven by them, suggesting potential causal pathways through which technology use may contribute to depression development. Conversely, escapism-motivated technology use showed stronger depression-to-technology effects, aligning with compensatory internet use theory [13] and suggesting that depression symptoms may lead individuals to increase technology use as a coping mechanism or escape from negative emotions. This pattern may represent a depression-driven technology engagement pathway that could potentially exacerbate or maintain symptoms over time. The study third hypothesis regarding BMI moderation was also supported, with stronger technology-to-depression effects among participants with overweight/obesity. This finding extends previous research linking both BMI and technology use to depression [19, 30] by suggesting that individuals with higher BMI may be particularly vulnerable to the potentially depressogenic effects of certain technology use patterns. Several mechanisms may explain this moderation effect, including heightened vulnerability to social comparison processes, increased sensitivity to sleep disruption, and potential interactions with body image concerns [8]. Several important clinical and theoretical implications emerge from the findings. First, the pattern-specific nature of technology-depression relationships suggests that interventions should target specific technology use dimensions rather than focusing on total usage time. For instance, restricting night-time technology use and addressing social-comparison behaviors may be particularly effective for depression prevention, while interventions for individuals already experiencing depression may need to address escapism-motivated use and provide alternative coping strategies. Second, the stronger technology-to-depression effects among participants with overweight/obesity highlight the importance of considering weight status in both assessment and intervention approaches. Weight management programs may benefit from addressing technology use patterns, while depression interventions for individuals with higher BMI may need to specifically target technology-related behaviors. Third, the findings suggest that digital literacy programs should include components addressing the potential mental health implications of specific technology use patterns. Educational interventions teaching mindful technology use, healthy digital boundaries, and awareness of social comparison triggers may help mitigate depression risk among university students.

The strong technology-to-depression pathway for social-comparison-motivated use merits particular consideration within the Chinese cultural context, where the concept of "face" (mianzi) and social comparison processes may have distinct implications. In collectivistic Chinese culture, maintaining face—one's social image and status—is particularly important, and social comparison serves as a key mechanism for evaluating one's standing [7]. The prevalence of digital social comparison among Chinese university students may be exacerbated by cultural emphasis on academic and social achievement, creating a context where online social comparison may be especially detrimental to mental health. Recent research suggests that Chinese youth may be particularly vulnerable to negative social comparison on digital platforms due to the intersection of traditional collectivistic values with modern competitive academic and professional environments [18]. Additionally, the rapid socioeconomic transitions in contemporary China have created intergenerational differences in values and expectations, potentially intensifying young adults' concerns about social evaluation and status comparison [19]. These culturally specific factors may help explain why social-comparison-motivated technology use demonstrated particularly strong associations with subsequent depression in our sample of Chinese university students.

Strengths and limitations

This study has several strengths, including its longitudinal design, large sample size, high retention rate, measurement of multiple technology use dimensions, and application of advanced statistical methods (RI-CLPM) that distinguish between- from within-person effects. Furthermore, this study addresses important gaps in the literature by examining a non-Western population and investigating potential moderating factors. However, several limitations warrant consideration. First, despite the longitudinal design, the study cannot definitively establish causality due to potential unmeasured confounding variables. While cross-lagged panel models provide information about temporal precedence, which is one criterion for causality, they cannot rule out all alternative explanations for observed associations. The relationships identified should therefore be interpreted as suggestive of potential causal pathways rather than definitive evidence of causation. Second, technology use patterns were primarily assessed through self-report measures, which may be subject to recall bias. Future studies should incorporate objective measures (e.g., device tracking applications) alongside self-reports. Third, although we conducted measurement invariance testing that supported the comparability of our measures across time points, some measures (particularly the Technology Use Questionnaire) have limited validation evidence compared to more established clinical measures. Fourth, our operationalization of technology use patterns, while multidimensional, does not capture all potentially relevant aspects of digital engagement, such as passive versus active use or exposure to specific content types. Fifth, the observed effect sizes, while statistically significant, were generally small to moderate, suggesting that technology use is just one of many factors influencing depression trajectories. Sixth, our sample, while large and demographically diverse within the university student population, had a disproportionate representation of overweight/obese individuals (55.6%) compared to the general Chinese university student population, potentially affecting the generalizability of our findings. Finally, our analysis of BMI as a moderator, while revealing important differential susceptibility patterns, does not elucidate the specific mechanisms through which BMI influences technology-depression relationships. While the study has a 9-month follow-up period allowed examination of short-term effects, longer-term studies are needed to understand how technology-depression relationships evolve over extended periods. Finally, the sample was limited to university students in eastern China, potentially limiting generalizability to other populations and regions.

Future directions

Several avenues for future research emerge from our findings. First, experimental studies manipulating specific technology use patterns (e.g., randomized trials of night-time use restriction) could provide stronger causal evidence regarding technology-depression relationships. Second, studies incorporating more frequent assessments (e.g., ecological momentary assessment) could illuminate more proximal processes connecting technology use and mood fluctuations. Third, neuroimaging studies examining neural correlates of different technology use patterns in relation to depression may provide insights into underlying mechanisms. Finally, intervention studies targeting pattern-specific technology use should examine whether such approaches effectively reduce depression risk or improve symptoms among those already experiencing depression.

Conclusion

This longitudinal study demonstrates complex, pattern-specific bidirectional relationships between technology use and depression among Chinese university students. The findings reveal that certain technology use patterns (night-time use, social-comparison-motivated use) more strongly predict subsequent depression, while others (escapism-motivated use) are more strongly predicted by depression. Additionally, these relationships are moderated by BMI, with stronger adverse effects among individuals with overweight/obesity. These nuanced findings challenge simplistic narratives about technology-depression relationships and suggest the need for pattern-specific, personalized approaches to both assessment and intervention. As digital technology continues to permeate daily life, understanding these complex interrelationships will be increasingly crucial for promoting mental health among university students.

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Clinical trial number: not applicable.

Author's contributions
Yuting Zhan mainly contributed to this work, the authors with both being responsible for conceptualization, data analysis, and manuscript preparation. Xu Ding led the data collection effort and supervised the project. Both authors read and approved the final manuscript. Xu Ding revised the article.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study has been reviewed and approval by the Shandong First Medical University Review Committee (U.R.C.), who verified that all methods used in this study were carried out in line with the 1964 Helsinki declaration and its subsequent revisions or similar ethical standards, as well as the ethical requirements of the institutional research committee. Informed consent has been obtained from all subjects involved in this study to publish this paper.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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References

1. Buysse DJ, Reynolds CF, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193–213. https://doi.org/10.1016/0165-1781(89)90047-4.
2. Chen L, Wang L, Qiu XH, Yang XX, Qiao ZX, Yang YJ, Liang Y. Depression among Chinese university students: Prevalence and socio-demographic correlates. PLoS ONE. 2019;14(3): e0213438. https://doi.org/10.1371/journal.pone.0213438.
3. Chen Y, Gao Q, Rau PLP. Watching others' social media use: Development and validation of the Technology Use Questionnaire among Chinese university students. Comput Hum Behav. 2020;108: 106348. https://doi.org/10.1016/j.chb.2020.106348.
4. Christensen MA, Bettencourt L, Kaye L, Moturu ST, Nguyen KT, Olgin JE, Pletcher MJ, Marcus GM. Direct measurements of smartphone screen-time: Relationships with demographics and sleep. PLoS ONE. 2016;11(11): e0165331. https://doi.org/10.1371/journal.pone.0165331.
5. Coyne SM, Rogers AA, Zurcher JD, Stockdale L, Booth M. Does time spent using social media impact mental health?: An eight year longitudinal study. Comput Hum Behav. 2020;104: 106160. https://doi.org/10.1016/j.chb.2019.106160.
6. Elhai JD, Dvorak RD, Levine JC, Hall BJ. Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. J Affect Disord. 2017;207:251–9. https://doi.org/10.1016/j.jad.2016.08.030.
7. Enders CK. Missing not at random models for latent growth curve analyses. Psychol Methods. 2011;16(1):1–16. https://doi.org/10.1037/a0022640.
8. Fardouly J, Vartanian LR. Social media and body image concerns: Current research and future directions. Curr Opin Psychol. 2016;9:1–5. https://doi.org/10.1016/j.copsyc.2015.09.005.

9. Hamaker EL, Kuiper RM, Grasman RP. A critique of the cross-lagged panel model. Psychol Methods. 2015;20(1):102–16. https://doi.org/10.1037/a0038889.
10. Heffer T, Good M, Daly O, MacDonell E, Willoughby T. The longitudinal association between social-media use and depressive symptoms among adolescents and young adults: An empirical reply to Twenge et al. (2018). Clinical Psychological Science. 2019;7(3):462–70. https://doi.org/10.1177/2167702618812727.
11. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct Equ Modeling. 1999;6(1):1–55. https://doi.org/10.1080/10705519909540118.
12. Huang Q, Li Y, Huang S, Qi J, Shao T, Chen X, Liao Z, Lin S, Zhang X, Cai Y, Chen H. Smartphone use and sleep quality in Chinese college students: A preliminary study. Front Psych. 2020;11: 352. https://doi.org/10.3389/fpsyt.2020.00352.
13. Kardefelt-Winther D. A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. Comput Hum Behav. 2014;31:351–4. https://doi.org/10.1016/j.chb.2013.10.059.
14. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: Validity of a brief depression severity measure. J Gen Intern Med. 2001;16(9):606–13. https://doi.org/10.1046/j.1525-1497.2001.016009606.x.
15. Kwon M, Kim DJ, Cho H, Yang S. The smartphone addiction scale: Development and validation of a short version for adolescents. PLoS ONE. 2013;8(12): e83558. https://doi.org/10.1371/journal.pone.0083558.
16. Li Y, Zhao J, Ma Z, McReynolds LS, Lin D, Chen Z, Wang T, Wang D, Zhang Y, Zhang J, Fan F, Liu X. Mental health among college students during the COVID-19 pandemic in China: A 2-wave longitudinal survey. J Affect Disord. 2021;281:597–604. https://doi.org/10.1016/j.jad.2020.11.121.
17. Liu M, Wu L, Yao S. Dose-response association of screen time-based sedentary behaviour in children and adolescents and depression: A meta-analysis of observational studies. Br J Sports Med. 2018;52(15):949–57. https://doi.org/10.1136/bjsports-2016-097667.
18. Liu S, Xiao T, Yang L, Loprinzi PD. Exercise as an alternative approach for treating smartphone addiction: A systematic review and meta-analysis of random controlled trials. Int J Environ Res Public Health. 2019;16(20): 3912. https://doi.org/10.3390/ijerph16203912.
19. Luppino FS, de Wit LM, Bouvy PF, Stijnen T, Cuijpers P, Penninx BW, Zitman FG. Overweight, obesity, and depression: A systematic review and meta-analysis of longitudinal studies. Arch Gen Psychiatry. 2010;67(3):220–9. https://doi.org/10.1001/archgenpsychiatry.2010.2.
20. Przybylski AK, Weinstein N. A large-scale test of the Goldilocks Hypothesis: Quantifying the relations between digital-screen use and the mental well-being of adolescents. Psychol Sci. 2017;28(2):204–15. https://doi.org/10.1177/0956797616678438.
21. Scott DA, Valley B, Simecka BA. Mental health concerns in the digital age. J Soc Work Educ. 2019;55(3):564–73. https://doi.org/10.1080/10437797.2019.1586803.
22. Spitzer RL, Kroenke K, Williams JB, Löwe B. A brief measure for assessing generalized anxiety disorder: The GAD-7. Arch Intern Med. 2006;166(10):1092–7. https://doi.org/10.1001/archinte.166.10.1092.
23. Thorisdottir IE, Sigurvinsdottir R, Asgeirsdottir BB, Allegrante JP, Sigfusdottir ID. Active and passive social media use and symptoms of anxiety and depressed mood among Icelandic adolescents. Cyberpsychol Behav Soc Netw. 2019;22(8):535–42. https://doi.org/10.1089/cyber.2019.0079.
24. Valkenburg PM, Peter J, Walther JB. Media effects: Theory and research. Annu Rev Psychol. 2016;67:315–38. https://doi.org/10.1146/annurev-psych-122414-033608.
25. Vannucci A, Ohannessian CM. Social media use subgroups differentially predict psychosocial well-being during early adolescence. J Youth Adolesc. 2019;48(8):1469–93. https://doi.org/10.1007/s10964-019-01060-9.
26. Vogel EA, Rose JP, Roberts LR, Eckles K. Social comparison, social media, and self-esteem. Psychol Pop Media Cult. 2014;3(4):206–22. https://doi.org/10.1037/ppm0000047.
27. Wang W, Bian Q, Zhao Y, Li X, Wang W, Du J, Zhang G, Zhou Q, Zhao M. Reliability and validity of the Chinese version of the Patient Health Questionnaire (PHQ-9) in the general population. Gen Hosp Psychiatry. 2014;36(5):539–44. https://doi.org/10.1016/j.genhosppsych.2014.05.021.
28. World Health Organization. Depression and other common mental disorders: Global health estimates. World Health Organization. 2017. https://apps.who.int/iris/handle/10665/254610.
29. Yang J, Fu X, Liao X, Li Y. Association of problematic smartphone use with poor sleep quality, depression, and anxiety: A systematic review and meta-analysis. Psychiatry Res. 2022;311: 114513. https://doi.org/10.1016/j.psychres.2022.114513.
30. Zhang J, Paksarian D, Lamers F, Hickie IB, He J, Merikangas KR. Sleep patterns and mental health correlates in US adolescents. J Pediatr. 2021;228:235–43. https://doi.org/10.1016/j.jpeds.2020.08.042.
31. Zhou BF. Predictive values of body mass index and waist circumference for risk factors of certain related diseases in Chinese adults—study on optimal cut-off points of body mass index and waist circumference in Chinese adults. Biomed Environ Sci. 2002;15(1):83–96. https://doi.org/10.1046/j.1440-6047.11.s8.9.x.

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