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Research Article

Quality of Generative Artificial Intelligence Use and Adolescent Well-Being: Pathways via Happiness, Meaning, and Resilience in Southwest China

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Background

Evidence on adolescents' generative artificial intelligence (GenAI) use and its associations with mental health is mixed.

Objective

We aim to examine whether GenAI-use motivation is associated with psychological resilience, testing both parallel mediation through happiness and meaning and serial mediation via happiness → meaning.

Methods

Adolescents attending boarding high schools in Southwest China with an on-campus phone ban (N = 395) completed measures of GenAI-use motivation, happiness, meaning in life, and resilience. Weekly off-campus/home GenAI-use frequency was self-reported using a single ordinal item. GenAI was defined as content-generating artificial intelligence accessed via standalone tools or embedded features. Partial least squares structural equation modeling with bias-corrected and accelerated bootstrapping (5,000 resamples) estimated associations and indirect effects.

Results

Motivation was weakly associated with happiness (β = 0.128) and positively associated with meaning (β = 0.197); happiness was related to meaning (β = 0.535). The total indirect effect on resilience was β = 0.183 (95% CI = [0.085, 0.277]) via happiness (β = 0.050, 95% CI = [0.001, 0.093]), meaning (β = 0.098, 95% CI = [0.047, 0.156]), and happiness → meaning (β = 0.034, 95% CI = [0.001, 0.068]). Self-reported use frequency showed a weak negative association with resilience (β = −0.062). The model explained 61.3% of the variance in resilience (R^2 = 0.613).

Conclusion

Adolescents' motivation for using GenAI may be more informative than frequency alone. School-based GenAI literacy, supported by educator professional learning that promotes guided, goal-directed use, may help foster adolescents' meaning in life and psychological resilience.

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1. INTRODUCTION

Adolescents are adopting generative artificial intelligence (GenAI)—including both standalone, prompt-based generative tools/services and embedded conversational agents within platforms—more quickly than evidence has accumulated on the mental-health consequences. Recent evidence indicates that adolescents and young adults are using GenAI for mental-health advice and related support-seeking, highlighting the urgency of clarifying potential benefits and risks in this age group.[1]

Rather than treating exposure duration as a proxy for risk, this study examined why and how adolescents engage with GenAI—focusing on use motivation—and which psychological resources such engagement may cultivate. To situate our approach within the broader digital well-being literature, recent mapping work has documented the rapid expansion and diversification of digital addiction research, reinforcing calls to move beyond undifferentiated "screen time" toward more specific, activity- and mechanism-focused models.[2] This approach aligns with calls to move beyond screen time by modeling the quality and purpose of digital use directly.[3-6] It is also consistent with cross-national syntheses suggesting that digital activities differ substantially in how they relate to children's well-being, making activity type and purpose more informative than time alone.[7]

In our setting, on-campus phone bans mean that reported GenAI frequency primarily reflects off-campus/home use. Importantly, evidence on school phone policies and adolescent well-being is mixed, and restrictive policies may change where and when phones are used rather than uniformly improving well-being; therefore, we treated the policy context as a boundary condition rather than a mechanism in itself.[8] Given that our frequency measure was a single ordinal item, we interpreted frequency-related findings conservatively and emphasized motivational quality as the primary explanatory construct.[9] We therefore investigated links among motivation, happiness, meaning in life, and psychological resilience.

Grounded in Self-Determination Theory (SDT), need-supportive, value-congruent reasons for technology use (e.g., curiosity, mastery, and contribution) align more strongly with adaptive self-regulation and well-being than controlled motives.[10,11] Related perspectives emphasize self-regulation and differential susceptibility as boundary conditions for technology–well-being links.[12,13] Accordingly, we distinguished GenAI-use motivation—the quality of engagement—from GenAI-use frequency—the quantity of exposure.[6,14] To reduce conceptual ambiguity, we operationalized GenAI as prompt-based systems that generate content (e.g., text, images, audio, and code) using generative models, consistent with international guidance, while noting that adolescents may encounter GenAI as both standalone apps and embedded agents.[15,16] In this study, motivation spanned study support, mood repair/distraction, feeling understood/listened to, and occasional self-disclosure.

A resource perspective clarifies why motivationally healthy engagement should matter. The Conservation of Resources (COR) theory posits that people acquire and protect resources that accumulate to support adaptation.[17,18] The broaden-and-build theory predicts that positive affect widens thought–action repertoires and consolidates durable personal resources.[19] In adolescence, happiness (affective well-being) and meaning in life (purpose/significance) are robust correlates of positive adaptation and psychological resilience.[20-23] Conceptually, positive affect can provide bandwidth for reflection and goal alignment, which channels into stronger meaning. Recent syntheses suggest that motivationally structured digital engagement can cultivate affective and meaning-related resources among youth, consistent with this pathway.[6,24] In line with recent positive-psychology evidence, resilience and meaning-making processes are closely intertwined during late adolescence, supporting our decision to model meaning in life as a key resource alongside affective well-being.[25]

Equity and context guide interpretation. Because frequency primarily reflects off-campus use rather than supervised classroom time, we anticipated heterogeneity across grade, socioeconomic status, and ethnicity, given device access and study demands. We therefore included covariates, conducted sensitivity checks, and, consistent with our cross-sectional design, examined associations and refrained from causal claims. Figure 1 presents the conceptual model.

The present study tests a theory-constrained, fully mediated model that separates motivation from frequency and

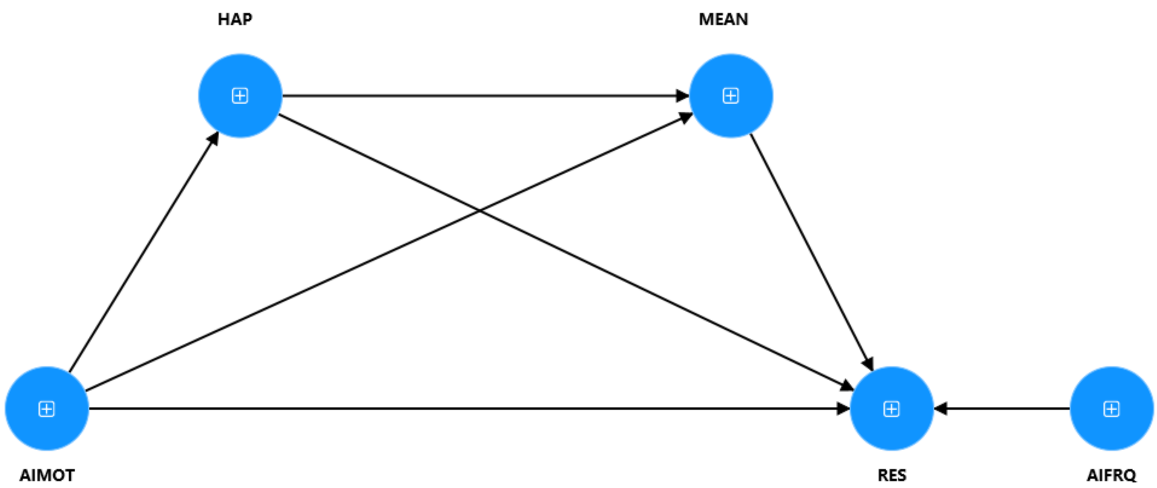

Figure 1. Conceptual model
Abbreviations: AIFRQ: Artificial intelligence-use frequency; AIMOT: Generative artificial intelligence-use frequency/motivation; HAP: Happiness; MEAN: Meaning in life; RES: Psychological resilience.

specifies happiness and meaning as parallel and serial (happiness → meaning) pathways to psychological resilience under phone-ban policies. We contribute by: (i) disentangling quality from quantity to identify which facet of GenAI use aligns with adolescent adaptation; (ii) formalizing a dual-route resource account (parallel routes and the happiness → meaning serial path) grounded in SDT and the COR theory; and (iii) providing equity-relevant evidence from an under-represented school context to inform culturally sensitive, prevention-oriented practice.

The hypotheses (H) of this study are as follows:

(i) **H1:** AIMOT is positively associated with HAP.
(ii) **H2:** HAP is positively associated with RES.
(iii) **H3:** AIMOT is positively associated with MEAN.
(iv) **H4:** MEAN is positively associated with RES.
(v) **H5:** HAP is positively associated with MEAN (serial link).
(vi) **H6:** AIFRQ is negatively associated with RES.
(vii) **H7:** AIMOT is indirectly associated with RES via HAP and MEAN, through parallel mediation (AIMOT → HAP → RES; AIMOT → MEAN → RES) and serial mediation (AIMOT → HAP → MEAN → RES).

2. MATERIALS AND METHODS

2.1. ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study complied with institutional and local regulations for research involving minors and adhered to the Declaration of Helsinki. Ethical approval was granted by the Institutional Research Ethics Committee of Leshan Normal University (Approval No. KYLL2025-10-03; approval date October 21, 2025). Prior to data collection, school leaders authorized site access. In accordance with school policy, parents/guardians were notified and consent was obtained, and students provided assent. Consent/assent materials explicitly stated that the survey included questions about students' GenAI use and related experiences. Surveys were anonymous and did not collect any personally identifying information. Data were stored on password-protected devices accessible only to the research team.

2.2. STUDY DESIGN AND SETTING

We conducted a cross-sectional, school-based survey in a county in Southwest China (Liangshan Yi Autonomous Prefecture). The region is multiethnic at the population level; however, individual students' ethnicity was not collected in this survey. Participating county public boarding high schools enforced on-campus phone-ban policies. Because phones are restricted on campus, students' reported GenAI engagement primarily reflects off-campus/home use rather than supervised classroom activities. We therefore treated the restricted-access setting as a boundary condition rather than a mechanism. We did not measure home-environment characteristics and thus did not interpret frequency as evidence of specific home-context processes. Under these policies, the frequency metric is indexed off-campus/home, less-structured engagement with GenAI as self-reported by students, rather than supervised classroom periods. GenAI was defined to participants as content-generating AI systems (text, images, audio, and code). These systems may be accessed via standalone tools/services or as embedded features within platforms. We noted that self-reports may not fully distinguish embedded AI features from standalone GenAI tools. Consistent with the conceptual framework, the *a priori* model specified GenAI-use motivation (AIMOT) → happiness (HAP) and meaning in life (MEAN) → psychological resilience (RES), with GenAI-use frequency (AIFRQ) entered as a distinct predictor of RES to examine motivational quality and use frequency as distinct correlates of resilience in this policy context.

2.3. PARTICIPANTS AND PROCEDURE

Class advisors introduced the study during homeroom. Interested students completed paper-and-pencil questionnaires in a scheduled session under teacher supervision; a researcher was present to clarify procedural (not content) questions. Inclusion criteria were enrollment in Grades 10–12 at participating high schools, provision of student assent, and, per school policy, parental/guardian consent. Exclusion criteria included self-reported vision or reading difficulties that would preclude survey completion and patterned or invalid responses on quality-check items. After screening, 395 questionnaires were retained (see Section 2.5). We report basic participant characteristics collected in the survey (grade level, gender, boarding status, and perceived family economic status). Information on urban/rural background and ethnicity was not collected in this dataset.

2.4. MEASURES

All multi-item constructs were modeled reflectively and administered in Chinese using 7-point Likert scales (1 = strongly disagree to 7 = strongly agree); higher scores indicate higher latent levels. Items were adapted to the school context, translated and back-translated, and cognitively checked.[26] Unless otherwise noted, scale scores were computed as the mean of available items (computed if ⩾75% of items were answered). All items were positively worded; no reverse-keyed items were used.

2.4.1. GENERATIVE ARTIFICIAL INTELLIGENCE

In this study, GenAI refers to content-generating AI systems that can generate text, images, audio, or code, accessed either as standalone tools/services or as embedded features within digital platforms. This definition distinguishes GenAI from generic web browsing or passive social media consumption, while acknowledging that adolescents' self-reports may not cleanly separate embedded AI features from standalone GenAI tools.

2.4.2. GENERATIVE ARTIFICIAL INTELLIGENCE-USE MOTIVATION (AIMOT)

Guided by SDT,[10,11,27] AIMOT captured need-supportive reasons for engaging with GenAI via six reflective indicators: study support, mood repair, distraction from worries, feeling understood, feeling listened to when venting, and occasional self-disclosure. Example stems include "I use GenAI tools to help me study" and "I feel that GenAI tools can listen when I need to vent my feelings." During administration, locally familiar examples were provided to aid comprehension; the construct targets motivational quality rather than attachment to any single brand.

2.4.3. HAPPINESS (HAP)

Four items adapted from the Subjective Happiness Scale assessed affective well-being.[28]

2.4.4. MEANING IN LIFE (MEAN)

Four items from the Meaning in Life Questionnaire–Presence dimension captured perceived purpose and significance.[23]

2.4.5. PSYCHOLOGICAL RESILIENCE (RES)

Four items adapted from the Connor–Davidson Resilience Scale and the Brief Resilience Scale reflected regulation, recovery, composure, and perseverance under stress.[29,30]

2.4.6. GENERATIVE ARTIFICIAL INTELLIGENCE-USE FREQUENCY (AIFRQ)

A single ordinal item indexed weekly off-campus/home GenAI engagement over the past week: "Over the past week, about how much time did you spend using generative AI tools outside school hours and off campus?" Response bands were 1 = rarely/never, 2 = <1 h, 3 = 1–3 h, 4 = 4–6 h, 5 = >6 h (coded increasing). Because concrete time/frequency is singular and directly reportable, AIFRQ was treated as a manifest exogenous predictor; internal-consistency indices were not applicable. We acknowledge that this single-item, ordinal measure was coarse and might have introduced reporting error; therefore, any frequency–resilience association was interpreted as a small correlational signal rather than a definitive dose–response effect.

2.5. DATA QUALITY AND PREPARATION

Questionnaires were excluded if they included (i) uniform straight-lining across pages, (ii) failed attention checks, or (iii) >20% missing answers. For retained cases, item-level missingness was low; when a respondent answered ⩾75% of a scale's items, person-mean imputation was used for occasional missing items; otherwise, the scale score was set to missing. Items were oriented so that higher values reflect higher trait levels. Variables were z-standardized for descriptive plots only (not for model estimation). We report complete-case structural equation modeling (SEM) results (N = 395). Because AIFRQ was a single-item ordinal indicator, it was analyzed as a manifest predictor without imputation or reliability correction.

2.6. STATISTICAL ANALYSIS

Relationships were estimated with partial least squares SEM (PLS-SEM) in SmartPLS 4 (SmartPLS GmbH, Germany) using bias-corrected and accelerated (BCa) bootstrapping with 5,000 resamples (two-tailed). The sign-changes option was set to none. Measurement quality was evaluated using indicator loadings, composite reliability, and average variance extracted (AVE). Discriminant validity was examined using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio of correlations (HTMT), and inner variance inflation factor (VIF) was inspected to rule out problematic collinearity. Structural paths are reported as standardized coefficients (β) with BCa 95% confidence intervals (CIs), alongside R^2 for endogenous constructs and Cohen's f^2 for local effect sizes. Predictive relevance was assessed using blindfolding Q^2, where appropriate, and PLS out-of-sample prediction error was profiled against a linear benchmark. Model discrepancy indices (standardized root mean square residual [SRMR], squared Euclidean distance [d_ULS], and Geodesic distance [d_G]) were provided descriptively. Indirect effects were tested for the parallel (via happiness; via meaning) and serial (happiness → meaning) routes, and the single-item AIFRQ indicator entered the model as an ordinal-coded, exogenous manifest predictor. AIFRQ categories were entered using monotonic numeric coding (1–5) for parsimony; estimates were interpreted as approximate linear associations across ordered categories. Covariates and sensitivity checks followed the a priori analysis plan to support robust inference.[31-36] We selected PLS-SEM because the study aimed to estimate a prediction-oriented mediation model with multiple indirect paths, a mix of latent constructs, and a single-item ordinal predictor. The approach relies on bootstrap inference rather than distributional assumptions. Given the cross-sectional design, all modeled paths were interpreted as associations rather than causal effects. Parallel and serial indirect effects were evaluated via bootstrapped confidence intervals.

3. RESULTS

3.1. SAMPLE CHARACTERISTICS

We analyzed 395 valid questionnaires (Table 1). Girls constituted 55.7% of the sample, and 87.1% of participants boarded at school. Students were primarily in Grade 10 (36.7%) and Grade 11 (49.9%), with 13.4% in Grade 12. Weekly off-campus/home GenAI use was generally low (36.5% rarely/never; 48.9% < 1 h; 12.2% 1–3 h; 1.0% 4–6 h; 1.5% > 6 h). Most participants self-reported an average economic status (58.2%), with 39.5% indicating some financial difficulty (9.1% very difficult; 30.4% relatively difficult). Device policies were highly restrictive: 92.4% were completely prohibited in class; 6.6% were prohibited in class, allowed after class; and 1.0% were freely allowed.

3.2. MEASUREMENT MODEL (REFLECTIVE)

Standardized loadings were mostly ⩾ 0.70; two marginal indicators (AIMOT1 = 0.663; HAPPY2 = 0.684) were retained given construct-level adequacy (Table 2). Internal consistency and convergent validity were satisfactory (composite reliability = 0.903/0.866/0.855/0.870 for AIMOT/HAP/MEAN/RES, respectively; AVE = 0.609/0.620/0.596/0.626, respectively). Indicator-level collinearity was not problematic (VIF range = 1.324–2.901). Discriminant validity was held under the Fornell–Larcker criterion and HTMT (Tables 3 and 4).

The standardized root mean square residual indicated acceptable global fit (SRMR_estimated = 0.074; SRMR_saturated = 0.073; both < 0.08). Conservative bootstrap discrepancy tests flagged potential misfit (d_ULS_estimated = 1.038, 95% Heterotrait–Monotrait confidence interval [HI95] = 0.561; d_G_estimated = 0.315, HI95 = 0.201; SRMR HI95 = 0.054). A normed fit index of 0.795 was reported for completeness. Given the known stringency of composite-based SEM, these indices were interpreted descriptively; construct quality and predictive evaluation guided adequacy judgments.

Table 1. Sample characteristics (*N* = 395)

Variable	Category	*n*	%
Gender	Male	175	44.3
	Female	220	55.7
Grade	Grade 10	145	36.7
	Grade 11	197	49.9
	Grade 12	53	13.4
Boarding status	Yes	344	87.1
	No	51	12.9
Weekly time using generative AI (after school / at home)	Rarely or never use	144	36.5
	< 1 hour	193	48.9
	1–3 hours	48	12.2
	4–6 hours	4	1.0
	> 6 hours	6	1.5
Perceived family economic status	Very difficult	36	9.1
	Relatively difficult	120	30.4
	Average	230	58.2
	Relatively affluent	6	1.5
	Very affluent	3	0.8
School device policy (mobile/tablet)	Completely prohibited in class	365	92.4
	Prohibited in class, allowed after class	26	6.6
	Freely allowed	4	1.0

Note: Percentages are based on valid responses (*N* = 395); totals may not equal 100% due to rounding.
Abbreviation: AI: Artificial intelligence.

Table 2. Reflective measurement model: loadings, reliability, and convergent validity

Construct & item	Loading	VIF	CR	α	AVE
GenAI-use motivation (AIMOT)			0.903	0.873	0.609
AIMOT1	0.663	1.324			
AIMOT2	0.798	2.088			
AIMOT3	0.877	2.671			
AIMOT4	0.843	2.901			
AIMOT5	0.736	2.396			
AIMOT6	0.745	2.325			
Happiness (HAP)			0.866	0.796	0.620
HAPPY1	0.869	2.102			
HAPPY2	0.684	1.449			
HAPPY3	0.810	1.636			
HAPPY4	0.775	1.529			
Meaning in life (MEAN)			0.855	0.774	0.596
MEAN1	0.761	1.486			
MEAN2	0.797	1.638			
MEAN3	0.738	1.506			
MEAN4	0.791	1.657			
Psychological resilience (RES)			0.870	0.801	0.626
RES1	0.821	1.722			
RES2	0.727	1.477			
RES3	0.800	1.590			
RES4	0.812	1.771			

Notes. Loadings are standardized. Retention rule: primary indicators ⩾ 0.70; marginal indicators (0.40–0.70) retained when CR and AVE remain adequate. Consistent partial least squares were used.[31]
Abbreviations: α: Cronbach's alpha; AVE: Average variance extracted; CR: Composite reliability; GenAI: Generative artificial intelligence; VIF: Inner variance inflation factor.

Table 3. Discriminant validity based on the Fornell-Larcker criterion

Construct	AIMOT	HAP	MEAN	RES
AIMOT	0.780			
HAP	0.128	0.787		
MEAN	0.266	0.560	0.772	
RES	0.169	0.664	0.712	0.791

Notes: Bootstrap resamples = 5,000; Sign-changes option = none.[32,37]
Abbreviations: AIMOT: Generative artificial intelligence-use motivation; HAP: Happiness; MEAN: Meaning in life; RES: Psychological resilience.

Table 4. Discriminant validity based on HTMT

Construct	AIMOT	HAP	MEAN	RES
AIMOT				
HAP	0.112			
MEAN	0.304	0.688		
RES	0.185	0.797	0.899	

Abbreviations: AIMOT: Generative artificial intelligence-use motivation; HAP: Happiness; HTMT: Heterotrait–Monotrait ratio of correlations; MEAN: Meaning in life; RES: Psychological resilience.

3.3. STRUCTURAL MODEL

Motivational quality showed no direct association with resilience (AIMOT → RES, β ≈ 0, 95% CI = [−0.077, 0.080]), but indirect effects were observed. Paths from the mediators to resilience were positive: for MEAN → RES, β = 0.498 (95% CI = [0.401, 0.588]), and for HAP → RES, β = 0.391 (95% CI = [0.302, 0.477]). The hypothesized link between happiness and meaning was also positive: HAP → MEAN, β = 0.535 (95% CI = [0.442, 0.615]). For first-stage paths from motivation, AIMOT → HAP (β = 0.128, 95% CI = [0.000, 0.235]) was small and borderline, and AIMOT → MEAN (β = 0.197, 95% CI = [0.098, 0.296]) was positive. GenAI-use frequency showed a small negative association with resilience (AIFRQ was measured with a single ordinal item; therefore, this coefficient should be interpreted *cautiously*) (AIFRQ → RES, β = −0.062, 95% CI = [−0.127, −0.002]). See Figure 2 and Table 5.

Specific indirect effects supported parallel mediation via happiness (β = 0.050, 95% CI = [0.001, 0.093]) and via meaning (β = 0.098, 95% CI = [0.047, 0.156]), as well as a serial path through happiness → meaning (β = 0.034, 95% CI = [0.001, 0.068]). The total indirect effect from motivation to resilience was β = 0.183 (95% CI = [0.085, 0.277]). The direct path from motivation to resilience was not supported (β ≈ 0, 95% CI = [−0.077, 0.080]).

3.4. EXPLANATORY AND PREDICTIVE METRICS

Explained variance (R^2) was 0.016 for happiness, 0.352 for meaning, and 0.613 for resilience (substantial for resilience) (Figure 2). The low R^2 for happiness indicates that the model explained only a small proportion of variance in happiness, which should be considered when interpreting the serial (happiness → meaning) route. Key local effect sizes were large for HAP → MEAN (f^2 = 0.434) and MEAN → RES (f^2 = 0.416), and medium for HAP → RES (f^2 = 0.269). Collinearity diagnostics were acceptable (see VIF range in Section 3.2). Table 6 summarizes these explanatory/predictive metrics.

4. DISCUSSION

4.1. PRINCIPAL FINDINGS

Across public boarding schools in Southwest China operating under on-campus phone bans, motivation for GenAI use was indirectly related to psychological resilience through happiness and meaning in life, while the direct path was null. Indirect effects were supported via meaning (β = 0.098)

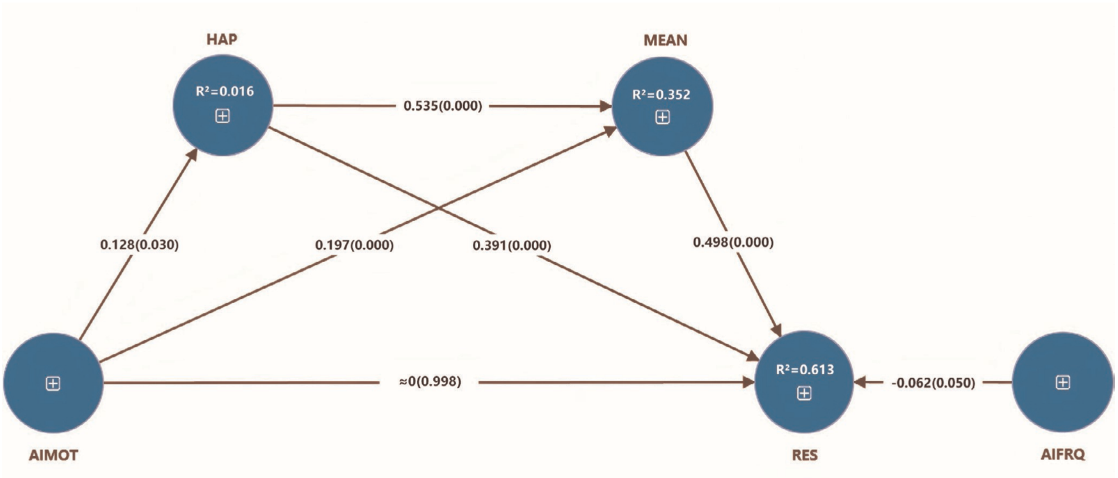

Figure 2. Final structural model estimated using partial least squares structural equation modeling.
Note: Standardized path coefficients (β) with 95% bias-corrected and accelerated bootstrapping confidence intervals.
Abbreviations: AIFRQ: Generative artificial intelligence-use frequency; AIMOT: Generative artificial intelligence-use motivation; HAP: Happiness; MEAN: Meaning in life; RES: Psychological resilience.

Table 5. Structural model results: direct, total, and specific indirect effects

Hypothesis	Relation	β	95% BCa CI Lower limit	Upper limit	Conclusion
H1	AIMOT → HAP	0.128	0.000	0.235	Supported
H2	HAP → RES	0.391	0.302	0.477	Supported
H3	AIMOT → MEAN	0.197	0.098	0.296	Supported
H4	MEAN → RES	0.498	0.401	0.588	Supported
H5	HAP → MEAN	0.535	0.442	0.615	Supported
H6	AIFRQ → RES	−0.062	−0.127	−0.002	Supported (small negative)
	AIMOT → RES (direct path)	≈0	−0.077	0.080	Not supported
H7	AIMOT → RES (via HAP & MEAN)	0.183	0.085	0.277	Supported
	AIMOT → HAP → RES	0.050	0.001	0.093	Supported
	AIMOT → MEAN → RES	0.098	0.047	0.156	Supported
	AIMOT → HAP → MEAN → RES	0.034	0.001	0.068	Supported

Notes: Data estimated using partial least squares structural equation modeling. β = Standardized path coefficient; Bootstrap resamples = 5,000; Sign-changes option = none.
Abbreviations: AIFRQ: Generative artificial intelligence-use frequency; AIMOT: Generative artificial intelligence-use motivation; BCa: Bias-corrected and accelerated bootstrap; HAP: Happiness; MEAN: Meaning in life; RES: Psychological resilience.

Table 6. Explanatory metrics and diagnostics (merged): R^2, key Cohen's f^2, and collinearity (VIF)

Measure	Estimate	Interpretation/Note
Explained variance (endogenous constructs)		
R^2, HAP	0.016	Low explained variance for happiness
R^2, MEAN	0.352	Moderate explained variance for meaning
R^2, RES	0.613	Substantial explained variance for resilience
Key effect sizes (Cohen's f^2; displayed paths only)		
HAP → MEAN	0.434	Large
MEAN → RES	0.416	Large
HAP → RES	0.269	Medium
Collinearity diagnostics		
Indicator VIF range (all indicators)	1.324–2.901	<5 indicates acceptable collinearity

Notes: R^2 summarizes explained variance of endogenous constructs; Cohen's f^2 profiles local effect sizes for displayed paths; VIF indicates inner-model collinearity.
Abbreviations: AIFRQ: Generative artificial intelligence-use frequency; AIMOT: Generative artificial intelligence-use motivation; HAP: Happiness; MEAN: Meaning in life; RES: Psychological resilience; VIF: Variance inflation factor.

and via the serial happiness → meaning routes (β = 0.034), although the serial route should be interpreted in light of the low explained variance in happiness (R^2_HAP = 0.016). Paths from happiness and meaning to resilience were positive (MEAN → RES, β = 0.498; HAP → RES, β = 0.391), and HAP → MEAN (β = 0.535) supported a serial link. GenAI-use motivation positively predicted both happiness and meaning in life (β = 0.128 and 0.197, respectively). Frequency of GenAI use showed a small negative association with resilience (β = −0.062). Because frequency was measured with a single ordinal self-report item indexing off-campus/home use, this association should be interpreted cautiously and not as evidence of a dose–response effect.

Resilience demonstrated substantial explanatory power in the model (R^2_RES = 0.613), with large local effects for HAP → MEAN and MEAN → RES, and medium for HAP → RES. These results align with our theory-constrained, fully mediated model and were interpreted as associations rather than causal claims. The restricted-access setting was treated as a boundary condition for interpretation, rather than a mechanism producing the observed associations. This focus on motivational quality complements evidence that some adolescents use GenAI for well-being–relevant purposes.[1] Taken together, the findings suggest that in this restricted-access context, adolescents' motivation for engaging with GenAI provides more insight into resilience-related resources (especially meaning-related) than the frequency of their reported use.

4.2. INTERPRETING THE DUAL-ROUTE RESOURCE ACCOUNT

The pattern of indirect associations is theoretically coherent. Within SDT, autonomous, need-supportive reasons for technology use predict affective well-being and purpose alignment, explaining links from GenAI-use motivation to happiness and meaning in life.[10,11] The broaden-and-build theory clarifies why happiness matters: positive affect widens thought–action repertoires, consolidating durable resources over time.[19] The COR theory treats meaning as a relatively stable asset that buffers stress and supports adaptation.[17,18] In our model, happiness was positively associated with meaning in life, which in turn was positively associated with resilience; this supports a plausible serial ordering (happiness → meaning) while remaining consistent with alternative temporal orderings that cannot be resolved with cross-sectional data. Given the small R^2 for happiness, the "first step" of the serial route appears weakly explained by the current predictors; the serial indirect effect should therefore be viewed as statistically supported but modest in explanatory contribution. These interpretations are consistent with recent syntheses on motivationally structured digital engagement among youth. Recent GenAI-specific evidence on adolescents' use (e.g., conversational agents and advice-seeking) further motivates distinguishing motivational quality from exposure metrics.[1,16] Prior work also links resilience with adolescents' meaning-making, consistent with the central role of meaning in our mediation pattern.[25]

4.3. A WEAK FREQUENCY–RESILIENCE ASSOCIATION IN A RESTRICTED-ACCESS CONTEXT

Under phone-ban policies, our frequency item primarily indexed off-campus, less-structured use; in this context, frequency was slightly negatively correlated with resilience (β = −0.062). Because we did not measure the home environment, and self-reports may not separate standalone tools from embedded AI features, explanations should remain tentative. A plausible account is time displacement (sleep, homework, and in-person interaction) and self-regulatory load, consistent with boundary-condition perspectives on differential susceptibility and self-regulation.[10,12,13,38,39] Importantly, the effect size was small, and the frequency indicator was coarse; thus, this result should be read as a weak association rather than a robust risk signal. This pattern is compatible with evidence that school device policies can shape usage patterns and correlates, underscoring the need for replication across policy regimes.[8] Finally, GenAI-specific dependency measures may capture risk-relevant variance more directly than time-based indicators.[9]

4.4. CONTEXT AND GENERALIZABILITY

Students in these Southwest China boarding schools follow strict routines and have limited, supervised digital access during the school day. Purposeful, reflective GenAI use may align with cultural emphases on balance and self-discipline, facilitating its translation into meaning and positive emotion, whereas habitual or avoidant use may conflict with these norms and yield small net losses. Because we did not directly measure cultural values or school climate, such interpretations should be treated as contextual hypotheses rather than tested explanations. Policy and culture, therefore, bound generalizability and motivated replication in schools without phone bans and in other cultural contexts.[10,38,39] More broadly, international reports on children's digital lives emphasize that associations can vary by context, platform affordances, and measurement choices, supporting the present focus on motivational quality.[7] Accordingly, school device policies may shift usage patterns and correlates rather than producing uniform effects.[7,8]

4.5. METHODOLOGICAL NOTES AND MODEL ADEQUACY

The theory-constrained PLS-SEM (SmartPLS 4; 5,000 BCa bootstraps) yielded acceptable SRMR (0.074) and substantial explanatory power (R^2_RES = 0.613), with positive Q^2 across endogenous constructs; discrepancy indices (d_ULS, d_G) were reported descriptively. GenAI was defined for participants as content-generating AI; weekly off-campus frequency was captured with a single ordinal item. Given rapid changes in GenAI integration into search and social platforms, self-reports may blend standalone tools with embedded features; this measurement limitation is most relevant to interpreting the frequency coefficient. These choices prioritize construct clarity and predictive relevance while aligning with reporting conventions that emphasize effect sizes and out-of-sample considerations.[6] Here, we emphasize that PLS-SEM estimates associations and indirect effects under the specified model; it does not establish temporal precedence or causal mechanisms. Adolescents' reactions to platform-embedded chatbots illustrate why "GenAI use" is heterogeneous and difficult to measure with brief self-reports.[16] This broader literature also underscores the value of precise construct definitions when extending digital well-being work to GenAI.[2]

4.6. PRACTICAL IMPLICATIONS

For education, efforts should move beyond blanket limits and prioritize GenAI literacy and reflective-use coaching—goal setting, mastery-oriented tasks, and structured reflection—to build happiness and meaning as malleable resources. In this restricted-access context, the most actionable implication is to support teachers in guiding students' purposeful GenAI engagement during permitted periods (e.g., off-campus/home), rather than focusing solely on reducing time. Teacher professional development can emphasize brief, repeatable routines: (i) a one-sentence "use goal" before prompting, (ii) a short checklist to verify outputs (accuracy, sources, and bias), (iii) a simple learning log noting what GenAI changed in understanding or strategy, and (iv) a 30-second reflection prompt linking use to personal goals/values. Targeted support may be warranted for high-frequency unstructured users and students primarily motivated by emotion regulation. Given the coarse frequency measure, "high frequency" should be treated as a screening cue rather than a diagnostic label.

For design, features that support autonomy, empathetic feedback, and creative scaffolding can steer engagement toward purposeful rather than compulsive use, complementing youth-focused artificial intelligence and digital mental health guidance.[3,10,11,16,38-40] These recommendations align with emerging guidance for GenAI in education and with calls to focus on quality of engagement rather than time alone.[15] Public health guidance similarly emphasizes developmentally appropriate guardrails and adult guidance for adolescent engagement with artificial intelligence.[38] Given evidence that some adolescents seek mental health advice from GenAI,[1] teacher training should also cover safety norms and referral pathways for sensitive use cases.

4.7. LIMITATIONS AND FUTURE DIRECTIONS

The cross-sectional design yields correlational evidence; causal claims are unwarranted. All constructs were self-reported, raising common-method concerns. The frequency measure was a single ordinal item tied to off-campus use, and the operationalization emphasized content-generating GenAI; results may not generalize to other modalities. We also lacked detailed sociodemographic indicators (e.g., urban/rural residence and ethnicity) and did not measure family digital supervision, limiting contextual inference and subgroup analyses.

Future work should deploy longitudinal or experimental designs to test parallel and serial mechanisms over time, integrate objective usage traces and multi-informant data, and examine moderators (gender, grade, socioeconomic status, and ethnicity) to identify the most significant pathway.[10,38,39] Given the low R^2 for happiness, future models should consider additional upstream predictors (e.g., baseline affect, stress, sleep, and peer support) to better explain happiness and to test whether the serial route is robust. Finally, replication across schools with different phone policies and across platforms with varying degrees of embedded GenAI would clarify the boundary conditions of the frequency–resilience association.[7,8] Future studies should also test which school- and family-level supports best implement recommended guardrails for adolescent GenAI engagement.[38] Where feasible, incorporating GenAI-specific measures of dependency or problematic use may improve risk detection beyond coarse time indicators.[9]

5. CONCLUSION

Adolescents' motives for using GenAI may be relevant to psychological resilience correlates, alongside use frequency. In boarding high schools in Southwest China with an on-campus phone ban, GenAI-use motivation was associated with happiness and meaning in life. In the same model, happiness and meaning in life were positively associated with psychological resilience. The overall pattern was consistent with parallel indirect pathways via happiness and via meaning in life, with more tentative evidence for a serial happiness → meaning in life pathway. In practice, school-based GenAI literacy—supported by educator professional learning that promotes guided, goal-directed use—may help inform schools' efforts to support adolescents' meaning in life and psychological resilience. Given the cross-sectional, self-report design (including a single ordinal measure of use frequency) and the restricted-access context (a boundary condition), causal inference and generalizability are unwarranted; future longitudinal or experimental studies incorporating objective use traces and multi-informant data are needed.

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CONFLICT OF INTEREST

The authors declare no competing interests.

AUTHOR CONTRIBUTIONS

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ETHICAL APPROVAL AND CONSENT TO PARTICIPATE

Ethical approval was obtained from the Institutional Research Ethics Committee of Leshan Normal University (approval no.: KYLL2025-10-03; date: Oct 21, 2025). Written informed consent was obtained from parents/guardians, and written assent was obtained from all adolescent participants.

CONSENT FOR PUBLICATION

The authors confirm that parental/guardian consent and student assent covered the use of anonymous data for research reporting and publication.

DATA AVAILABILITY STATEMENT

The data are available from the corresponding author upon reasonable request.

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