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Resilience as a shield: protective and risk factors in a mediation model of cyberbullying among Thai secondary students

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ABSTRACT

This study examined cyberbullying among 366 lower secondary students in Northern Thailand, confirming a four-component model (masquerade (MAS), exclusion (EXC), harassment (HAR), and outing (OUT)) with excellent empirical fit. Structural equation modeling revealed resilience as the strongest protective factor against cyberbullying behaviors (β=-0.282), while authoritarian parenting (AUT) emerged as a significant risk factor (β=0.195). AUT undermined self-esteem (β=-0.162) and social relationships (β=-0.267). Self-esteem proved to be a powerful resilience builder (β=0.578). Media influence showed a direct negative relationship with cyberbullying (β=-0.196) while diminishing resilience. Resilience functioned as a partial mediator between AUT and cyberbullying (variance accounted for (VAF)=0.201), demonstrating how harsh parenting indirectly increases cyberbullying risk by eroding psychological coping mechanisms. Resilience served as a complete mediator between self-esteem and cyberbullying (VAF=0.891), revealing that healthy self-perception primarily protects against cyberbullying by strengthening psychological resilience. Additionally, resilience operated as a competitive mediator in pathways involving social networks and media influence.

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1. INTRODUCTION

Cyberbullying differs from traditional bullying through its use of rapidly evolving technology and accessible online platforms [1]. Unlike face-to-face bullying, it allows offenders to conceal their identity and harm victims without witnessing physical responses [2]. This anonymity enables targeting across locations and time zones, making regulation extremely challenging and creating continuous cycles of escalating violence. Thai youth under 22 spend an average of 8 hours and 24 minutes online daily, increasing their cyberbullying exposure and victimization risk [3]. This aggressive behavior involves individuals or groups using electronic devices to transmit harmful messages or images [4], [5]. Research identifies seven cyberbullying components [6], namely: flaming (hostile messages), harassment (repeated offensive communication), cyberstalking (threats), denigration (harmful statements), impersonation (pretending to be others), outing (OUT) (sharing personal information), and exclusion (isolating from online groups). Among Thai adolescents, cyberbullying manifests through four dimensions: masquerade (MAS) (95% prevalence), exclusion (EXC), harassment (HAR), and information disclosure [7]. The Thai cultural context presents unique dimensions to cyberbullying. Traditional values emphasizing respect for authority and conflict avoidance create distinctive manifestations of online aggression. Thailand's hierarchical society and emphasis on group harmony over individual confrontation produce different cyberbullying expressions compared to other countries. Most concerning, former victims often become perpetrators seeking revenge, aligning with previous research [8] identifying revenge as a primary motivation, perpetuating cycles of digital violence.

Despite continuous cyberbullying research, some causal relationships remain overlooked with contradictory findings. This research addresses three critical gaps: limited investigation of resilience as a mediating variable between environmental factors and cyberbullying behaviors in non-Western contexts; insufficient examination of complex interplay between Thai cultural values, parenting styles, and digital behaviors; and methodological limitations in previous studies employing traditional statistical approaches ill-suited to the emergent, multidimensional nature of cyberbullying constructs. Cyberbullying stems from complex interactions between psychological, familial, and social factors. Resilience serves as a key protective factor, defined by Grotberg [9] as the capacity to recover from difficulties and adapt positively to challenges. Werner [10] identified four critical resilience characteristics: problem-focused coping, positive temperament, effective challenge management, and self-control perception, which strengthen resistance to harmful digital behaviors. Self-esteem development significantly influences how adolescents interact online. Coopersmith [11] describes healthy self-esteem as demonstrating assertiveness, confidence, and positive social engagement. However, the relationship with cyberbullying is complex, while low self-esteem increases vulnerability to becoming perpetrators and victims, artificially inflated self-esteem may drive aggressive online behaviors as compensation [12].

Parenting approaches crucially shape resilience and self-esteem development. Authoritarian parenting (AUT), characterized by strict control with limited emotional responsiveness [13], often fails to nurture self-regulation skills necessary for appropriate online conduct. Schaefer [14] identified three critical dimensions, acceptance-rejection, firm-lax control, and psychological autonomy-control, that determine whether family environments foster or inhibit cyberbullying tendencies. These family influences operate within broader media contexts that shape adolescent behavior. Potter [15] described six interconnected media effects: cognitive, beliefs, attitudes, affective, physiological, and behavioral, which collectively normalize or challenge aggressive digital behaviors. This media influence interacts with family dynamics, potentially reinforcing or countering authoritarian messages. These factors manifest within adolescents' social relationships. Hinduja and Patchin [16] indicated that strong positive attachments create social bonds that inhibit cyberbullying by increasing perceived social costs of antisocial behaviors. Kowalski *et al.* [17] identified key protective relationship qualities including emotional support, trust, and intimacy, which collectively protect adolescents from engaging in cyberbullying behaviors.

An analysis of 24 studies reveals that internal psychological resources, particularly self-esteem (25% of studies) and resilience (21% of studies), function as foundational elements within this ecosystem. These factors interact with AUT approaches (29% of studies) and media influences (33% of studies). The anticipated results of this research suggest a sophisticated pattern where these factors interact dynamically. Self-esteem and resilience are expected to demonstrate significant negative relationships with cyberbullying behaviors [18]–[21] with resilience functioning as a crucial mediating variable that not only directly reduces cyberbullying tendencies but also buffers negative impacts of AUT and harmful media messages. The interactive nature of these relationships means that efforts to address one factor in isolation will likely prove insufficient; effective intervention requires addressing multiple elements of this ecosystem simultaneously. Social relationships further moderate these dynamics, with positive connections providing models for positive conflict resolution that counter aggressive approaches potentially learned through AUT or media exposure. To comprehensively address these questions, the study employs statistical methods including confirmatory composite analysis (CCA) to examine the measurement structure of cyberbullying, an emergent variable whose properties cannot be explained by examining individual variables in isolation [22]. Partial least squares structural equation modeling (PLS-SEM) offers superior predictive capabilities for complex behavioral phenomena and greater flexibility in handling both reflective and formative measurement models simultaneously.

This research focuses specifically on factors influencing cyberbullying among lower secondary school students who are experiencing significant physical, intellectual, emotional, and social changes making them particularly vulnerable to adjustment crises. The study addresses two specific research questions:

i) What are the direct effects of media influence, authoritarian parenting, peer relationships, and self-esteem on cyberbullying behaviors among Thai secondary school students?
ii) To what extent does resilience mediate the relationship between these predictive factors and cyberbullying behaviors?

The results will contribute to developing more effective, culturally appropriate interventions that address the complex interplay of factors shaping cyberbullying behaviors in the Thai context and potentially other collectivist societies facing similar challenges in the digital age.

2. RESEARCH METHOD
2.1. Sample and data collection
This study examined the measurement structure of various variables to determine the appropriate sample size for analysis. In CCA and PLS-SEM, sample size calculation was based on parameter estimation properties, using an effect size (f^2) of 0.25, statistical power of 80%, 9 latent variables, 27 observed variables, 99% confidence level, and an acceptable margin of error of ±1%. The minimum required sample size was 281 participants, calculated using statistical tools from http://www.danielsoper.com/statcalc [23], [24].

The sample was obtained through proportional allocation sampling to ensure the sample distribution was representative of the population, comprehensively covering population characteristics and obtaining truly representative samples to prevent problems of insufficient or incomplete data. The final sample size was 366 participants, which was 30% more than the minimum requirement, drawn from 14 schools out of a population of 44 schools and 40 classrooms out of a population of 514 classrooms. Among these participants, female students outnumbered male students at 57.66% (n=211) while male students comprised 42.34% (n=155). By grade level, grade 9 students had the highest proportion at 36.61% (n=134), followed by grade 8 at 32.24% (n=118), and grade 7 at 31.15% (n=114).

The researchers established strict guidelines to protect the confidentiality and rights of participants throughout the data collection process. All participants received documentation explaining their rights, including the right to withdraw from the research at any time if they felt uncomfortable answering any questions. The researchers ensured that all data collected through questionnaires would be kept confidential. Upon receiving the completed questionnaires, the researchers excluded questionnaires with incomplete responses or repetitive answers throughout the entire questionnaire, resulting in 366 usable questionnaire sets. This systematic data collection method, combined with the ethical protection measures employed, ensured that the research was conducted with integrity and respect for participants' rights.

2.2. Instrumentation
This study employed a questionnaire on cyberbullying among lower secondary school students under the Lampang-Lamphun Secondary Educational Service Area Office. The instrument was developed through a review of literature, theoretical concepts, and previous research related to the study variables. The questionnaire consisted of 72 items organized into 3 sections.

The first section collected respondents' general information including gender, age, school, and daily social media usage through multiple-choice and fill-in formats. The second section assessed cyberbullying behaviors using 31 items measuring 12 indicators across four components. The third section examined factors influencing cyberbullying with 41 items covering 15 indicators within five latent variables. Both the second and third sections employed a 5-point rating scale ranging from "strongly agree/feel/behave" (5) to "hardly agree/feel/behave" (1). The instrument development begins with a comprehensive literature review to establish operational definitions. The researchers then constructed questionnaire items aligned with the measurement framework, with cyberbullying items distributed across four components: MAS (e.g., I have fabricated or embellished information about others on social media); EXC (e.g., I have deleted or blocked people I dislike from groups on social media); HAR (e.g., I often send repeated messages to annoy others through social media); and OUT (e.g., I think it's fun to share photos of others without permission on social media). Similarly, items related to influential factors measured five variables: resilience (e.g., I can control my emotions, distress, and various pressures), self-esteem (e.g., I believe my actions often produce the results I expect), media influence (e.g., I use novel, sometimes uncreative language from media in my daily life), AUT (e.g., My parents or guardians don't allow me opportunities to express my feelings), and relationships/networks (e.g., I have close friends with whom I can talk and share life stories). After initial development, the draft questionnaire was submitted to thesis advisors for feedback and subsequently revised. The improved version was then presented to four experts in educational research methodology and psychology to assess content validity. The experts evaluated the consistency between items and operational definitions using the index of item-objective congruence (IOC). Content validity analysis revealed that IOC values for cyberbullying items ranged from 0.50 to 1.00, while factors influencing cyberbullying ranged from 0.75 to 1.00, indicating acceptable to excellent content validity. Items with lower IOC values (0.50) were retained after considering their discrimination power in subsequent analyses.

The questionnaire underwent pilot testing with 110 non-sample lower secondary students from the same educational service area. Discrimination analysis using item-total correlation showed positive coefficients ranging from 0.230 to 0.816 for cyberbullying items. Independent sample *t*-tests comparing high and low scoring groups (33rd percentile) identified 17 of 31 cyberbullying items and 28 of 41 factor items with statistical significance. Reliability analysis using Cronbach's alpha coefficient revealed excellent internal consistency across both measurement sections. The cyberbullying section (CB) demonstrated an overall reliability of 0.918, with component reliabilities for MAS (spreading rumors, deception, impersonation) ranging from 0.762 to 0.801, EXC (blocking from groups, collective attacks, information concealment) from 0.815 to 0.883, HAR (sending offensive messages, provocative messages, sexual harassment) from 0.740 to 0.776, and OUT (revealing messages, data theft, sharing photos/videos) from 0.768 to 0.822. The factors section showed an overall reliability of 0.883, with individual factor reliabilities for resilience (RES: withstand pressure, hope and encouragement, and overcoming obstacles) ranging from 0.712 to 0.825, self-esteem (SEL: self-integrity, self-confidence, self-worth, and self-competence) from 0.830 to 0.882, AUT (parental communication, punishment, expectations) from 0.670 to 0.748, relationships/networks (relationships with peers, teachers, community) from 0.782 to 0.846, and media influence (EFF: media access, imitation behavior) from 0.654 to 0.710. The final selection of items was based on 3 criteria: positive discrimination coefficients, statistically significant differences between high and low groups at the 0.05 level, and component/factor reliability of 0.70 or higher. This rigorous development and validation process ensured that the instrument possessed strong psychometric properties suitable for measuring cyberbullying behaviors and their influential factors among lower secondary school students.

2.3. Analyzing of data

This study employed PLS-SEM to analyze causal relationships between multidimensional variables. Parameter estimation utilized the PLS algorithm, while statistical significance was determined through Bootstrap analysis with 5,000 iterations. The analysis addressed the high-order formative-formative model structure using ADANCO 2.3.2 software and the disjoint two-stage approach, which helped reduce complexity, prevent multicollinearity, minimize measurement errors, and enhance validity and reliability. The analytical process followed a systematic two-stage approach: first obtaining factor scores for lower-level variables, then using these scores as indicators for higher-level latent variables in the second stage. For overall model assessment, the study evaluated model fit using multiple criteria based on Schuberth *et al.* [25]: standardized root mean square residual (SRMR), geodesic discrepancy (d_G), and unweighted least squares discrepancy (d_{ULS}) values below HI99. If all 3 exceeded HI99, SRMR needed to be below 0.080 [26]. The measurement model (formative outer model) was assessed through CCA using Hair *et al.* [27] criteria: variance inflation factor (VIF) below 5.0 to check for multicollinearity, statistically significant indicator weights (t-weight>1.96), and for non-significant indicators, loading values exceeding 0.5. The structural model evaluation examined path coefficients for statistical significance [28], coefficient of determination R^2 values (0.25, 0.50, 0.75 indicating small, medium, large effects), effect sizes f^2 (0.02, 0.15, 0.35 representing small, medium, large effects), and predictive relevance Q^2 (>0, with 0.02, 0.15, 0.35 indicating small, medium, large predictive power).

The analysis employed a comprehensive mediation framework, examining both full and partial mediation effects to understand complex relationships between variables. Full mediation occurs when the independent variable's effect on the dependent variable operates entirely through the mediator, while partial mediation indicates that both direct and indirect pathways are significant. In addition to examining the direction and significance of effects, the study incorporated the variance accounted for (VAF) metric to quantify mediation strength. The VAF represents the proportion of the total effect (TE) explained by the indirect effect through the mediator. Generally, a VAF exceeding 0.8 indicates full mediation, a VAF between 0.2 and 0.8 suggests partial mediation, and a VAF below 0.2 implies minimal mediation despite statistical significance. In competitive mediation cases, it is important to note that VAF values may exceed 1 or become negative. Negative VAF occurs when direct and indirect effects have opposite signs, while VAF values exceeding 1 may arise when the magnitude of the indirect effect is larger than the TE. Both instances don't indicate analytical errors but rather signal competitive mediation, where both indirect and direct effects are significant but operate in opposing directions ($a \times b \times c<0$).

The study particularly focused on these competitive mediation scenarios, where 'a' represents the independent variable's effect on the mediator, 'b' denotes the mediator's effect on the dependent variable, and 'c' indicates the direct effect of the independent variable on the dependent variable. When these pathways counteract each other, they often produce non-significant TE as opposing influences cancel out. Rather than dismissing these relationships, the research validates the hypothesized mediator while suggesting additional mediators working in the opposite direction. Following Zhao *et al.* [29], the study prioritizes the significance of indirect effects through bootstrap testing, transforming potentially overlooked relationships into valuable theoretical insights that guide the identification of additional mediating mechanisms.

3. RESULTS AND DISCUSSION

The CCA revealed strong structural validity for the cyberbullying measurement model among middle school students. The first-order model demonstrated excellent fit with empirical data (SRMR=0.0384, d_{ULS}=0.1152, d_G=0.0476), well below the 0.08 threshold. Indicator weights ranged from 0.2421 to 0.6233, with all indicators showing statistical significance at p<.01. t-weight values for all indicators exceeded the critical threshold of 1.96, ranging from 2.6543 (HAR2) to 9.1655 (EXC2), confirming their statistical significance. The highest weights were observed for EXC2 (0.6233, t=9.1655), MAS1 (0.4661, t=5.2556), and HAR1 (0.4622, t=6.6162). Multicollinearity assessment yielded VIF values between 1.1228 and 1.6446, all below the critical threshold of 3, confirming the absence of multicollinearity issues. Similarly, the second-order formative-formative model displayed strong consistency with empirical data, with indicator weights of 0.3131 across all four components (MAS, EXC, HAR, and OUT) and remarkably high t-weight values (56.3677), demonstrating their robust statistical significance, as shown in Table 1. Loading values ranged from 0.7889 to 0.8061, further validating the hierarchical measurement structure of cyberbullying.

Table 1. CCA results for first-order and second-order measurement models of cyberbullying

Construct	Indicator	First-order				Second-order			
		Weight	t-weight	Loading	VIF	Weight	t-weight	Loading	VIF
MAS	MAS1	0.4661	5.2556	0.8276	1.4451	0.3131	56.3677	0.7889	1.6559
	MAS2	0.3823	4.0322	0.8240	1.6078				
	MAS3	0.3881	4.2280	0.7712	1.3911				
EXC	EXC1	0.3673	5.7818	0.6146	1.1228	0.3131	56.3677	0.7966	1.7117
	EXC2	0.6233	9.1655	0.8649	1.3269				
	EXC3	0.3179	4.1008	0.7398	1.3953				
HAR	HAR1	0.4622	6.6162	0.8082	1.4067	0.3131	56.3677	0.8061	1.7582
	HAR2	0.2421	2.6543	0.7618	1.6446				
	HAR3	0.5191	6.2670	0.8515	1.5026				
OUT	OUT1	0.3008	4.0281	0.7187	1.3911	0.3131	56.3677	0.8022	1.7175
	OUT2	0.3962	5.2327	0.7824	1.4283				
	OUT3	0.5569	7.1864	0.8508	1.3132				

The PLS-SEM analysis examining factors influencing cyberbullying behavior showed satisfactory model fit (SRMR=0.0469, d_{ULS}=0.4187, d_G=0.1153). According to Hu and Bentler criteria [26], the SRMR value below 0.08 confirms adequate model fit. The second-order structural model revealed varying statistical significance among predictor variables. Within the CB construct, EXC showed the highest weight (0.5019, t=1.8778), followed by HAR (0.5261, t=1.9711), MAS (0.1716, t=0.6092), and OUT (0.0727, t=0.3657). Although these t-weight values fell below the critical threshold of 1.96 (indicating non-significant weights at p<.05), Hair *et al.* [27] methodological guidelines recommend a two-stage assessment process for formative indicators. When weight significance fails to meet criteria, researchers should examine the indicators' absolute contribution through their loadings. In this study, the substantial loading values for these factors (EXC=0.8451, HAR=0.7921, MAS=0.6950, and OUT=0.5486) all exceeded the 0.5 threshold criterion, providing sufficient evidence to retain these indicators in the model despite their non-significant weights. This approach acknowledges that indicators can still make meaningful contributions to their constructs even when their relative importance (weights) appears statistically non-significant. The strongest predictor variables demonstrated robust statistical significance, particularly media exposure (MEDA: weigh=0.8465, t=10.9092), hope (HOPE: weight=0.5101, t=6.8612), experiential factors (EXPE: weigh=0.7873, t=3.8905), and family communication (COMU: weight=0.5860, t=5.7138), all well above the critical t-value of 1.96 (p<0.05). Multicollinearity assessment yielded VIF values ranging from 1.0007 to 2.6505, all below the critical threshold of 3 recommended by Hair *et al.* [27] confirming the absence of multicollinearity issues among predictor variables, as shown in Table 2.

The analysis of standardized regression coefficients (β) in the structural equation model revealed variables that differed significantly from zero and exerted both positive and negative influences on CB. At the 0.01 significance level, RES and AUT demonstrated significant effects with varying magnitudes (β=-0.2821 and 0.1948, respectively). EFF also showed a significant negative effect on cyberbullying at the 0.05 significance level (β=-0.1959). However, SEL and REL did not significantly differ from zero (β=-0.0427, p-value=0.6501 and β=0.0647, p-value=0.3747, respectively), indicating these two factors had no direct influence on cyberbullying among lower secondary school students.

When examining the TE of factors influencing CB, RES, and AUT had significant effects in negative and positive directions respectively at the 0.01 significance level, while SEL showed a significant negative effect at the 0.05 level. EFF did not have a significant TE on cyberbullying, though it did have a significant direct negative effect (DE=-0.1959, p<0.05). These variables collectively explained 13.0% of the variance in cyberbullying (R^2adj=0.130). The REL variable had no significant effect on cyberbullying. Among the significant factors, RES exhibited the strongest TE (TE=-0.2821), followed by AUT (TE=0.2286) and SEL (TE=-0.2059). It is worth noting that self-esteem's effect on cyberbullying was primarily indirect (IE=-0.1632, p<0.01) rather than direct.

Regarding factors influencing RES, SEL showed a significant positive direct effect at the 0.01 significance level. While the direct effect of AUT on resilience was not significant, its TE showed a significant negative influence at the 0.05 level, primarily through indirect pathways. EFF demonstrated a significant negative direct effect at the 0.05 level. These 3 factors jointly explained 45.20% of the variance in resilience (R^2_{adj}=0.452). Additionally, AUT exhibited significant negative direct effects at the 0.01 significance level on both SEL and REL, explaining 2.60% (R^2_{adj}=0.026) and 7.20% (R^2adj=0.072) of their variance, respectively, as shown in Table 3 and Figure 1. The analysis examined direct, indirect, and TE in the structural equation model, testing RES as a mediating variable between various factors and CB among lower secondary school students. Statistical significance was determined using the Bootstrap method through the ADANCO program. Mediating variables were evaluated using Baron and Kenny approach [30], complemented by VAF assessment to determine the level and type of mediation effect.

Table 2. CCA results for first-order and second-order measurement models

Construct	Indicator	First-order				Second-order			
		Weight	*t*-weight	Loading	VIF	Weight	*t*-weight	Loading	VIF
MAS	MAS1	0.4551	2.3081	0.6430	1.0793	0.1716	0.6092	0.6950	2.1000
	MAS2	0.1346	0.4785	0.5881	1.3317				
	MAS3	0.7154	3.1749	0.8780	1.3119				
EXC	EXC1	0.6882	1.8412	0.9310	1.6573	0.5019	1.8778	0.8451	2.0868
	EXC2	0.2332	1.1408	0.5456	1.2065				
	EXC3	0.2910	0.7194	0.8166	1.8389				
HAR	HAR1	0.5880	2.2072	0.7409	1.0519	0.5261	1.9711	0.7921	1.3158
	HAR2	0.4349	1.6607	0.5814	1.0327				
	HAR3	0.4861	1.3916	0.6407	1.0411				
OUT	OUT1	0.4441	1.1469	0.6528	1.0759	0.0727	0.3657	0.5486	1.3992
	OUT2	0.5810	1.6775	0.7603	1.0771				
	OUT3	0.4327	1.0925	0.6202	1.0576				
RES	WITH	0.1755	1.7656	0.6728	1.4799	0.2421	3.1471	0.7086	1.4799
	HOPE	0.4893	6.0445	0.8688	1.5878	0.5101	6.8612	0.8762	1.5878
	OVER	0.5097	5.1064	0.8962	1.8333	0.4371	5.0058	0.8727	1.8333
SEL	INTE	0.2380	2.1010	0.7793	1.8525	0.1745	1.9866	0.7529	1.8525
	CONF	0.2427	1.6057	0.8594	2.6505	0.2947	2.6615	0.8759	2.6505
	WORT	0.2642	1.9407	0.8134	2.0731	0.2950	2.8482	0.8320	2.0731
	COMP	0.4468	3.9534	0.8752	1.7956	0.4217	4.3119	0.8657	1.7956
AUT	COMM	0.5688	2.9893	0.5488	1.0215	0.5651	3.5546	0.5252	1.0215
	PUNT	0.2671	0.7562	0.6702	1.4461	0.1096	0.4171	0.5815	1.4461
	EXPE	0.6602	1.9686	0.7707	1.4430	0.7873	3.8905	0.8122	1.4430
REL	PEER	0.1068	0.7480	0.5393	1.3398	0.1422	1.1300	0.5705	1.3398
	TEAR	0.5677	4.4680	0.7871	1.3543	0.5764	5.2318	0.8040	1.3543
	COMU	0.6197	5.1665	0.7997	1.1005	0.5860	5.7138	0.7772	1.1005
EFF	MEDA	0.8485	9.7511	0.8622	1.0007	0.8465	10.9092	0.8602	1.0007
	IMBE	0.5068	3.7675	0.5296	1.1740	0.5101	4.1718	0.5329	1.1740

Table 3. Path analysis results of direct, indirect and TE in the structural model

Path	DE	IE	TE	Cohen's f^2
The explained variance of the CB variable (R^2_{adj}=0.130)				
RES→CB	-0.2821**	-	-0.2821**	0.0500
SEL→CB	-0.0427	-0.1632**	-0.2059*	0.0009
EFF→CB	-0.1959*	0.0312	-0.1647	0.0377
AUT→CB	0.1948**	0.0338	0.2286**	0.0403
REL→CB	0.0647	-0.0169	0.0478	0.0029
The explained variance of the RES variable (R^2_{adj}=0.452)				
SEL→RES	0.5785**	-	0.5785**	0.3766
EFF→RES	-0.1106*	-	-0.1106*	0.0195
AUT→RES	-0.0466	-0.1099**	-0.1565*	0.0037
REL→RES	0.0598		0.0598	0.0040
The explained variance of the SEL variable (R^2_{adj}=0.026)				
AUT→SEL	-0.1623**	-	-0.1623**	0.0270
The explained variance of the REL variable (R^2_{adj}=0.072)				
AUT→REL	-0.2674**	-	-0.2674**	0.0770

Note: ***p*-value＜0.01, **p*-value＜0.05, DE: direct effect, IE: indirect effect, TE: total effect

When examining resilience as a mediator between AUT and cyberbullying, the results showed that with resilience in the model, the direct effect significantly decreased at the 0.01 significance level (C=0.2052, C'=0.1883). The indirect effect was 0.0473, statistically significant at the 0.01 level. The VAF value fell between 0.20-0.80 (VAF=0.201), indicating that resilience served as a partial mediator in this relationship.

Resilience functioned as a full mediator between SEL and cyberbullying, with the direct effect becoming non-significant when resilience was included (C=-0.1152, p<0.05; C'=-0.0229, p>0.05). The indirect effect was significant (IE=-0.1882, p<0.01) with a VAF of 0.891, demonstrating that self-esteem influences cyberbullying primarily through resilience.

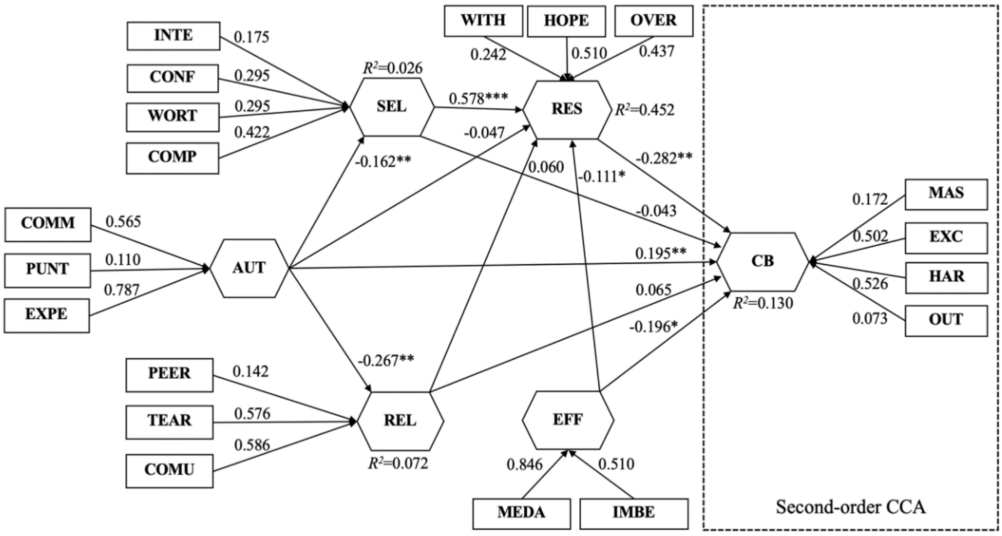

Figure 1. Path model of AUT, REL, SEL, EFF and RES on CB with second-order CCA results

For REL and cyberbullying, resilience functioned as a competitive mediator (VAF=5.304). The direct effect changed from non-significant positive (C=0.0227) to a stronger positive relationship (C'=0.0904), while the indirect effect was significantly negative (IE=-0.1114, p<0.01), suggesting opposing mechanisms. Similarly, resilience acted as a competitive mediator between EFF and cyberbullying (VAF=-0.721). The direct effect became more negative with resilience in the model (C=-0.1870, p<0.05; C'=-0.1964, p<0.05), while the indirect effect was significantly positive (IE=0.0823, p<0.01), indicating counteracting pathways.

The analysis also examined sequential mediation pathways. The results showed no significant mediation for AUT→self-esteem→resilience→cyberbullying (VAF=0.122, IE=0.0292, and p>0.05) or AUT→relationships→resilience→cyberbullying (VAF=0.026, IE=0.0057, and p>0.05). These findings confirm that resilience plays diverse mediating roles in the relationships between various factors and cyberbullying behaviors among lower secondary school students, functioning as a partial, full, or competitive mediator depending on the specific pathway examined, as shown in Table 4.

This study illuminates the complex dynamics of cyberbullying among lower secondary students in Northern Thailand, revealing resilience as the decisive protective factor while AUT emerges as a significant risk factor. Our findings uncover crucial psychological pathways that shape cyberbullying vulnerability through varied mediation patterns, offering important theoretical and practical insights for addressing this growing concern in Thai adolescent digital behavior. The analysis revealed three distinct mediation patterns through which resilience influences cyberbullying behavior, creating a comprehensive picture of how psychological and social factors interact in the digital landscape of Thai adolescents.

Resilience functions as a partial mediator between AUT and cyberbullying behaviors. This pattern indicates that AUT influences cyberbullying through two distinct pathways: directly increasing cyberbullying tendencies and indirectly undermining psychological resilience that would otherwise protect against such behaviors. The persistence of a significant direct effect suggests that strict control with limited emotional responsiveness directly promotes cyberbullying behaviors through modeling aggressive problem-solving approaches, limiting empathy development, and reducing self-regulation skills. This finding aligns with Zurcher *et al.* [31] research demonstrating how AUT creates family dynamics that fail to nurture crucial self-regulation skills necessary for appropriate online conduct. Similarly, Moreno–Ruiz *et al*. [32] found that adolescents from authoritarian homes often demonstrate higher aggression tendencies that manifest in digital environments. Simultaneously, the significant indirect path demonstrates how AUT erodes psychological coping mechanisms that buffer against engaging in harmful online behaviors. As noted by Baumrind [13], when parents emphasize obedience without explanation and employ punishment without warmth, adolescents develop limited capacity for constructive problem-solving and emotional regulation, key components of resilience as defined by Werner [10]. This dual influence creates a cascading effect where AUT undermines both self-esteem and social relationships, two essential protective resources for adolescents navigating digital environments. In the Thai cultural context, where traditional hierarchical values emphasize obedience and discipline, these negative effects may be particularly pronounced as adolescents lack alternative models for constructive conflict resolution and emotional regulation [1].

Table 4. Results of the mediating role of resilience in the relationship between AUT and cyberbullying

Path	Effect	β	t-value	VAF (IE/TE)	Conclusion
AUT→CB	TE	0.2356	3.5623**	0.201	Partial mediation
AUT→CB	DE(C)	0.2052	3.8295**		
AUT→CB	DE(C')	0.1883	2.7781**		
AUT→RES→CB	IE	0.0473	2.4527**		
SEL→CB	TE	-0.2111	-2.9238**	0.891	Full mediation
SEL→CB	DE(C)	-0.1152	-1.8279*		
SEL→CB	DE(C')	-0.0229	-0.2654		
SEL→RES→CB	IE	-0.1882	-3.4054**		
REL→CB	TE	-0.0210	-0.3633*	5.304	Competitive mediation
REL→CB	DE(C)	0.0227	0.3478		
REL→CB	DE(C')	0.0904	1.4188		
REL→RES→CB	IE	-0.1114	-3.1192**		
EFF→CB	TE	-0.1141	-1.3968	-0.721	Competitive mediation
EFF→CB	DE(C)	-0.1870	-1.9689*		
EFF→CB	DE(C')	-0.1964	-2.3084*		
EFF→RES→CB	IE	0.0823	3.3245**		
AUT→CB	TE	0.2383	3.6274**	0.122	No mediation
AUT→CB	DE(C)	0.2052	3.8295**		
AUT→CB	DE(C')	0.2091	0.29730**		
AUT→SEL→RES→CB	IE	0.0292	1.6032		
AUT→CB	TE	0.2216	3.1994**	0.026	No mediation
AUT→CB	DE(C)	0.2052	3.8295**		
AUT→CB	DE(C')	0.2159	3.1178**		
AUT→REL→RES→CB	IE	0.0057	0.3542		

Note: ***p*-value<0.01, **p*-value<0.05

In contrast to the partial mediation observed with AUT, resilience completely mediates the relationship between self-esteem and cyberbullying. This complete mediation reveals that healthy self-perception protects against cyberbullying entirely by strengthening psychological resilience rather than through direct mechanisms. The strong positive relationship between self-esteem and resilience demonstrates how positive self-evaluation serves as a powerful resilience builder, providing adolescents with the psychological fortitude needed to navigate online challenges constructively. This finding extends previous research [20], [21], by identifying the specific pathway through which self-esteem manifests its protective benefits. When Thai adolescents possess healthy self-perception, they develop greater capacity for constructive problem-solving, emotional regulation, and adaptive coping, core components of resilience that shield against engaging in digital aggression [18]. As Coopersmith [11] observed, individuals with healthy self-esteem demonstrate assertiveness, confidence, and positive social engagement. The findings clarify that these qualities primarily protect against cyberbullying by strengthening psychological resilience rather than through direct effects, highlighting the crucial intervening role of psychological fortitude in translating positive self-perception into appropriate online behavior.

The analysis uncovered intriguing competitive mediation patterns for both media influence and social relationships with cyberbullying, where direct and indirect effects operate in opposite directions, creating counteracting forces within the same pathways. This phenomenon aligns with Zhao *et al.* [29] conceptualization that competitive mediation occurs when opposing mechanisms operate simultaneously within the same model. Media influence demonstrates a direct negative relationship with cyberbullying while simultaneously diminishing resilience capacity. This paradoxical pattern suggests that media exposure provides direct protection against cyberbullying, perhaps through awareness of consequences or digital citizenship education, while simultaneously undermining the psychological resources that would otherwise protect against harmful online behaviors. This dual nature echoes Potter [15] description of six interconnected media effects (cognitive, beliefs, attitudes, affective, physiological, and behavioral) that collectively may produce contradictory outcomes. Similarly, social relationships exhibit competing influences: strengthening resilience (which protects against cyberbullying) while potentially normalizing certain cyberbullying behaviors within peer groups. Research has consistently demonstrated how positive connections to peers create protective bonds [33], but our findings suggest these same relationships may contain risk elements that operate through separate pathways. This competitive dynamic helps explain why peer relationships show complex and sometimes contradictory associations with cyberbullying in previous research [34].

These findings illuminate why cyberbullying represents such a challenging phenomenon, the same factors can simultaneously protect and promote cyberbullying through different mechanisms. As Zhao *et al.* [29] suggest, such competitive mediation often signals omitted mediators in the direct path, perhaps media literacy or critical thinking skills that develop through media engagement but operate independently of general resilience. Cyberbullying emerges from an intricate ecosystem of psychological, familial, and social influences rather than isolated risk factors. This aligns with Zych *et al.* [35] recognition that cyberbullying research has evolved from descriptive studies to sophisticated analyses of multifaceted causal relationships. AUT creates vulnerability both directly and by undermining self-esteem and social relationships, two essential protective resources. Self-esteem builds resilience, which provides crucial protection against digital aggression. Media influence and social relationships operate through competing pathways, simultaneously offering protection and risk. This interconnected system explains why single-factor interventions often produce limited results. The identification of resilience as the central protective mechanism offers a promising intervention focal point, as enhancing psychological fortitude may buffer against multiple risk factors simultaneously [19].

4. CONCLUSION

This study presents several groundbreaking contributions to cyberbullying research that distinguish it from existing literature. First, we developed the first culturally-validated, four-component cyberbullying model specifically for Thai adolescents, revealing "MAS" behaviors (95% prevalence) as a unique cultural manifestation reflecting Thailand's emphasis on indirect communication and conflict avoidance, a pattern never systematically documented in cyberbullying research. Second, our structural equation modeling unveils the pivotal discovery that resilience functions as a central protective mechanism through 3 distinct mediation patterns: partial mediation with AUT, complete mediation with self-esteem, and competitive mediation with media influence and social relationships, fundamentally reframing cyberbullying as emerging from an intricate ecosystem of interconnected psychological, familial, and social influences rather than isolated risk factors.

Methodologically, this research advances the field by employing sophisticated CCA and PLS-SEM with a disjoint two-stage approach, specifically designed for formative-formative measurement models that traditional statistical approaches cannot adequately address. Our systematic examination of competitive mediation, where opposing mechanisms operate simultaneously within the same pathways, challenges conventional single-direction causality assumptions and explains why the same factors can simultaneously protect against and promote cyberbullying through different mechanisms. Theoretically, the identification of resilience as a "shield" that operates differently across various risk pathways provides unprecedented insights into why single-factor interventions often produce limited results.

Culturally, this study bridges traditional Thai hierarchical values with digital behavior manifestations, revealing how cultural emphasis on group harmony and authority respect creates distinctive expressions of online aggression. The discovery of an "ecosystem model" where AUT creates dual vulnerabilities, directly increasing cyberbullying tendencies while undermining protective psychological resources, offers revolutionary understanding for collectivist societies facing similar digital-age challenges. Practically, these findings demand immediate transformation from conventional intervention approaches toward comprehensive, multi-system frameworks that address the interconnected nature of cyberbullying risk factors, potentially revolutionizing prevention strategies not only in Thailand but across similar cultural contexts globally. Innovation significance: This research transforms cyberbullying from a behavioral problem to a complex cultural-psychological phenomenon, establishing new theoretical foundations for understanding digital aggression in non-Western contexts and creating empirically-validated pathways for culturally-responsive interventions that address root ecosystem dynamics rather than surface symptoms.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
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O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

All research activity by the authors included in the review have been undertaken with the approval of Chiang Mai University Ethics Committees, COA No. 062/66 CMUREC No. 66/073.

DATA AVAILABILITY

The data that support the findings of this study on factors affecting cyberbullying are available from the corresponding author [SD], upon reasonable request. The data are not publicly available due to privacy and ethical restrictions, as they contain information that could compromise the privacy of research participants, including personal information of students and individuals involved.

REFERENCES

[1] R. Sittichai and P. K. Smith, "Bullying in South-East Asian Countries: A review," *Aggression and Violent Behavior*, vol. 23, pp. 22–35, Jul. 2015, doi: 10.1016/j.avb.2015.06.002.

[2] R. Donegan, "Bullying and Cyberbullying: History, Statistics, Law, Prevention and Analysis," *The Elon Journal of Undergraduate Research in Communications*, vol. 3, no. 1, pp. 33–42, 2012.

[3] S. Hinduja and J. W. Patchin, "Cyberbullying: An Exploratory Analysis of Factors Related to Offending and Victimization," *Deviant Behavior*, vol. 29, no. 2, pp. 129–156, Jan. 2008, doi: 10.1080/01639620701457816.

[4] P. K. Smith, J. Mahdavi, M. Carvalho, S. Fisher, S. Russell, and N. Tippett, "Cyberbullying: its nature and impact in secondary school pupils," *Journal of Child Psychology and Psychiatry*, vol. 49, no. 4, pp. 376–385, Apr. 2008, doi: 10.1111/j.1469-7610.2007.01846.x.

[5] M. A. Campbell, "Cyber Bullying: An Old Problem in a New Guise?" *Australian Journal of Guidance and Counselling*, vol. 15, no. 1, pp. 68–76, Jul. 2005, doi: 10.1375/ajgc.15.1.68.

[6] N. E. Willard, *Cyberbullying and Cyberthreats: Responding to the Challenge of Online Social Aggression, Threats, and Distress*. Champaign, IL: Research Press, 2007.

[7] T. Tudkuea, K. Laeheem, and R. Sittichai, "Development of a causal relationship model for cyber bullying behaviors among public secondary school students in the three southern border provinces of Thailand," *Children and Youth Services Review*, vol. 102, pp. 145–149, Jul. 2019, doi: 10.1016/j.childyouth.2019.05.013.

[8] J. W. Patchin and S. Hinduja, "Cyberbullying and Self-Esteem*," *Journal of School Health*, vol. 80, no. 12, pp. 614–621, Dec. 2010, doi: 10.1111/j.1746-1561.2010.00548.x.

[9] E. H. Grotberg, "The international resilience research project," in *54th Annual Convention, International Council of Psychologists*, 1996, pp. 1–18. [Online]. Available: https://files.eric.ed.gov/fulltext/ED417861.pdf

[10] E. E. Werner, "Resilience in development," *Current Directions in Psychological Science*, vol. 4, no. 3, pp. 81–84, Jun. 1995.

[11] S. Coopersmith, *Coopersmith self-esteem inventories*. Palo Alto, CA: Consulting Psychologists Press, 1981, doi: 10.1037/t06456-000.

[12] G. Brewer and J. Kerslake, "Cyberbullying, self-esteem, empathy and loneliness," *Computers in Human Behavior*, vol. 48, no. 1, pp. 255–260, 2015.

[13] D. Baumrind, "Current patterns of parental authority.," *Developmental Psychology*, vol. 4, no. 1, pp. 1–103, Jan. 1971.

[14] E. S. Schaefer, "Children's Reports of Parental Behavior: An Inventory," *Child Development*, vol. 36, no. 2, p. 413, Jun. 1965.

[15] W. J. Potter, *Media Effects*. Thousand Oaks, CA: SAGE Publications, Inc., 2012.

[16] S. Hinduja and J. W. Patchin, "Social Influences on Cyberbullying Behaviors Among Middle and High School Students," *Journal of Youth and Adolescence*, vol. 42, no. 5, pp. 711–722, May 2013, doi: 10.1007/s10964-012-9902-4.

[17] R. M. Kowalski, G. W. Giumetti, A. N. Schroeder, and M. R. Lattanner, "Bullying in the digital age: A critical review and meta-analysis of cyberbullying research among youth.," *Psychological Bulletin*, vol. 147, no. 5, pp. 345–376, 2021.

[18] N. Auemaneekul, A. Powwattana, E. Kiatsiri, and N. Thananowan, "Investigating the mechanisms of theory of planned behavior on cyberbullying among Thai adolescents," *Journal of Health Research*, vol. 34, no. 1, pp. 42–55, Nov. 2019, doi: 10.1108/JHR-02-2019-0033.

[19] F. Kabadayi and S. V. Sari, "What is the Role of Resilience in Predicting Cyber Bullying Perpetrators and Their Victims?" *Journal of Psychologists and Counsellors in Schools*, vol. 28, no. 1, pp. 102–117, Jun. 2018, doi: 10.1017/jgc.2017.20.

[20] R. M. Kowalski and S. P. Limber, "Psychological, Physical, and Academic Correlates of Cyberbullying and Traditional Bullying," *Journal of Adolescent Health*, vol. 53, no. 1, pp. S13–S20, Jul. 2013, doi: 10.1016/j.jadohealth.2012.09.018.

[21] D. Santos, E. Mateos-Pérez, M. Cantero, and M. Gámez-Guadix, "Cyberbullying in adolescents: resilience as a protective factor of mental health outcomes," *Cyberpsychology, Behavior, and Social Networking*, vol. 24, no. 6, pp. 414–420, Jun. 2021, doi: 10.1089/cyber.2020.0337.

[22] J. Henseler and F. Schuberth, "Using confirmatory composite analysis to assess emergent variables in business research," *Journal of Business Research*, vol. 120, pp. 147–156, Nov. 2020, doi: 10.1016/j.jbusres.2020.07.026.

[23] J. F. Hair. Jr., L. M. Matthews, R. L. Matthews, and M. Sarstedt, "PLS-SEM or CB-SEM: updated guidelines on which method to use," *International Journal of Multivariate Data Analysis*, vol. 1, no. 2, pp. 107–123, 2017, doi: 10.1504/IJMDA.2017.087624.

[24] J. C. Westland, "Lower bounds on sample size in structural equation modeling," *Electronic Commerce Research and Applications*, vol. 9, no. 6, pp. 476–487, Nov. 2010, doi: 10.1016/j.elerap.2010.07.003.

[25] F. Schuberth, J. Henseler, and T. K. Dijkstra, "Partial least squares path modeling using ordinal categorical indicators," *Quality & Quantity*, vol. 52, no. 1, pp. 9–35, Jan. 2018, doi: 10.1007/s11135-016-0401-7.

[26] L. Hu and P. M. Bentler, "Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification.," *Psychological Methods*, vol. 3, no. 4, pp. 424–453, Dec. 1998, doi: 10.1037/1082-989X.3.4.424.

[27] J. F. Hair, C. M. Ringle, and M. Sarstedt, "PLS-SEM: Indeed a Silver Bullet," *Journal of Marketing Theory and Practice*, vol. 19, no. 2, pp. 139–152, Apr. 2011, doi: 10.2753/MTP1069-6679190202.

[28] J. Henseler, M. R. Christian, and R. R. Sinkovics, "The use of partial least squares path modeling in international marketing," *Advances in International Marketing*, vol. 20, pp. 277–319, 2009.

[29] X. Zhao, J. G. Lynch, and Q. Chen, "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis," *Journal of Consumer Research*, vol. 37, no. 2, pp. 197–206, Aug. 2010, doi: 10.1086/651257.

[30] R. M. Baron and D. A. Kenny, "The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations.," *Journal of Personality and Social Psychology*, vol. 51, no. 6, pp. 1173–1182, 1986, doi: 10.1037/0022-3514.51.6.1173.

[31] J. D. Zurcher, H. G. Holmgren, S. M. Coyne, C. P. Barlett, and C. Yang, "Parenting and Cyberbullying Across Adolescence," *Cyberpsychology, Behavior, and Social Networking*, vol. 21, no. 5, pp. 294–303, May 2018, doi: 10.1089/cyber.2017.0586.

[32] D. Moreno–Ruiz, B. Martínez–Ferrer, and F. García–Bacete, "Parenting styles, cyberaggression, and cybervictimization among adolescents," *Computers in Human Behavior*, vol. 93, pp. 252–259, Apr. 2019, doi: 10.1016/j.chb.2018.12.031.

[33] H. Vandebosch and K. V. Cleemput, "Cyberbullying among youngsters: profiles of bullies and victims," *New Media & Society*, vol. 11, no. 8, pp. 1349–1371, Dec. 2009, doi: 10.1177/1461444809341263.

[34] H. J. Thomas, J. G. Scott, J. M. Coates, and J. P. Connor, "Development and validation of the Bullying and Cyberbullying Scale for Adolescents: A multi-dimensional measurement model," *British Journal of Educational Psychology*, vol. 89, no. 1, pp. 75–94, Mar. 2019, doi: 10.1111/bjep.12223.

[35] I. Zych, D. P. Farrington, and M. M. Ttofi, "Protective factors against bullying and cyberbullying: A systematic review of meta-analyses," *Aggression and Violent Behavior*, vol. 45, pp. 4–19, Mar. 2019, doi: 10.1016/j.avb.2018.06.008.

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