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Machine Learning Detection of Online Social Exclusion and Its Association with Adolescent Loneliness

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ABSTRACT

Objective: The present study aimed to examine whether machine learning–detected online social exclusion predicts adolescent loneliness and whether computationally derived exclusion indicators provide incremental explanatory power beyond self-reported perceived exclusion.

Methods and Materials: A cross-sectional correlational design was employed with a sample of 718 adolescents aged 13–17 years recruited from secondary schools in central Mexico. Participants completed the Spanish-adapted UCLA Loneliness Scale and a validated self-report measure of online social exclusion. In addition, anonymized digital interaction data from the previous 30 days were collected and processed using natural language processing techniques. A supervised transformer-based machine learning model was trained to classify exclusionary linguistic and interactional patterns within 96,438 message entries. Individual-level online exclusion probability scores were computed based on linguistic markers, response latency asymmetry, and unanswered message ratios. Hierarchical regression analyses and structural equation modeling were conducted to test direct and indirect associations between machine learning–detected exclusion, perceived exclusion, and loneliness.

Findings: Machine learning–detected online social exclusion was positively and significantly associated with adolescent loneliness ($p < 0.001$). Hierarchical regression analysis demonstrated that computationally detected exclusion predicted loneliness above and beyond demographic variables and self-reported exclusion ($\Delta R^2 = 0.06$, $p < 0.001$). Structural equation modeling indicated acceptable model fit and revealed that perceived exclusion partially mediated the relationship between machine learning–detected exclusion and loneliness (indirect effect $p < 0.001$), while the direct path remained significant ($p < 0.001$).

Conclusion: The findings indicate that algorithmically detected online exclusionary patterns constitute a significant and independent predictor of adolescent loneliness. Integrating machine learning–based behavioral analytics with psychosocial assessment enhances the precision of loneliness risk identification and offers promising avenues for early detection and prevention strategies in digitally mediated youth environments.

Keywords: *Adolescent loneliness, online social exclusion, cyber-ostracism, machine learning, digital mental health, computational psychology.*

1. Introduction

Loneliness during adolescence has emerged as a pressing global public health concern, with increasing empirical attention devoted to its antecedents, developmental trajectories, and psychosocial consequences. Adolescence represents a critical developmental period characterized by heightened sensitivity to peer acceptance, identity formation, and belongingness needs. When these needs are unmet, experiences of social exclusion and ostracism can intensify emotional vulnerability and internalizing symptoms. Recent large-scale investigations have demonstrated that adolescent loneliness is not merely a transient emotional state but a multidimensional construct associated with diminished psychological well-being, increased substance use, and academic disengagement (Tunkkari, 2025; Tunkkari et al., 2025). Longitudinal evidence further indicates that ostracism and loneliness operate synergistically, contributing to maladaptive outcomes across adolescence (Kiuru et al., 2024). The rapid digitalization of peer interaction has introduced new forms of exclusion, including cyber-ostracism, silent ignoring, and algorithmically mediated invisibility, thereby transforming the landscape of adolescent social experience.

Social ostracism, defined as being ignored or excluded by others, threatens fundamental psychological needs such as belonging, self-esteem, control, and meaningful existence. Empirical research across diverse populations confirms robust associations between ostracism and loneliness (Arslan & Yıldırım, 2021; Boykina et al., 2024). In adolescent contexts, ostracism experiences have been operationalized through psychometrically validated scales such as the Ostracism Experience Scale for Adolescents and Youth (Boykina et al., 2023), enabling more nuanced differentiation between chronic outsiderhood and situational exclusion. School-based studies demonstrate that perceived social outsiderhood predicts internalizing symptoms and school absenteeism, with internalizing processes mediating this association (Alanko et al., 2025). These findings underscore the psychosocial salience of exclusion experiences and their cumulative developmental implications.

The migration of adolescent social life to online environments complicates traditional understandings of ostracism. Digital platforms allow for asynchronous communication, visible metrics of social validation (e.g., likes, reactions), and quantifiable indicators of engagement or neglect. Experimental evidence suggests that being ignored online may elicit stronger need threats than overt rejection, as ambiguity amplifies perceived social invisibility (Lutz & Schneider, 2020). Cyber-ostracism has been linked to non-suicidal self-injury through mediating pathways involving depression and experiential avoidance (Ding et al., 2022). Similarly, cyber-victimization correlates with loneliness, moderated by social support and self-efficacy (Heiman & Olenik-Shemesh, 2022). These findings converge on the notion that digital exclusion is psychologically consequential and may operate through mechanisms partially distinct from offline rejection.

Loneliness itself is not monolithic. Comparative cross-cultural research has documented variability in loneliness prevalence across Southeast Asian student populations (Pangestika et al., 2024), suggesting contextual moderators such as collectivistic norms and digital communication patterns. Qualitative analyses of youth discussion forums reveal heterogeneity in loneliness narratives, ranging from existential isolation to situational peer disconnection (Kaarakainen et al., 2025). Thematic syntheses among youth with chronic physical conditions highlight overlapping experiences of social isolation and perceived difference (Miao et al., 2024; Sluiter et al., 2024). Moreover, psychological variables such as low self-control (Stavrova et al., 2021), affective warmth perception (Murphy, 2021), and personality traits including the Big Five (Kiran & Thiruchelvi, 2020) influence susceptibility to loneliness and ostracism experiences. Protective factors such as self-esteem and perceived social competence buffer against loneliness in ostracized adolescents (Sakız et al., 2020).

The interplay between social media use and loneliness remains complex. On one hand, digital platforms may facilitate belonging, peer support, and identity exploration, particularly among marginalized youth populations (Charmaraman et al., 2024). On the other hand, maladaptive patterns such as social comparison, fear of missing out, and compulsive engagement may exacerbate loneliness (Tang et al., 2023). Empirical work demonstrates that loneliness predicts the formation of online friendships, potentially reflecting compensatory social seeking (Dreslin & Hedrick, 2023). Simultaneously, narcissistic adolescents may engage in both antisocial and prosocial behaviors online in attempts to regulate loneliness and seek validation (Wang et al., 2023). The mediating role of gaming and social media in linking loneliness and psychological symptoms has also been documented (Bruneel, 2025; Risco & Mills, 2025). Such findings indicate bidirectional and potentially reinforcing relationships between digital engagement and loneliness.

Cyberbullying research further contextualizes online exclusion. Systematic investigations among school-going adolescents identify loneliness as both a risk factor and outcome of cyberbullying involvement (Olutola & Whitehouse, 2024; Razzaq, 2025). Variable-oriented and person-oriented analyses show that offline and online victimization experiences overlap yet demonstrate domain-specific psychological correlates (Burger & Bachmann, 2021). These studies emphasize the need to distinguish between active aggression and passive exclusion, as both may undermine belongingness but operate through distinct behavioral patterns.

Although psychological research has robustly established associations between ostracism and loneliness, measurement has traditionally relied on self-report instruments. Advances in computational social science now permit the integration of machine learning techniques to detect patterns of exclusion within digital communication data. Recent studies applying artificial intelligence to adolescent behavioral data demonstrate promise in identifying latent psychosocial risk factors (Pu & Gan, 2025; Razzaq, 2025). Big data approaches allow for scalable detection of linguistic markers, response latency asymmetries, and interactional imbalance. Such methodologies may complement self-report scales and reduce biases associated with subjective perception.

Theoretical frameworks further support integrating computational detection with psychosocial assessment. Need-threat theory posits that ostracism activates fundamental motivational systems. Self-determination perspectives highlight thwarted relatedness as central to loneliness development. Social network analyses demonstrate that network centrality and relational reciprocity correlate with subjective well-being (Webster et al., 2020). Moreover, awe and positive solitude experiences may buffer loneliness under certain circumstances (Jiang et al., 2023; Yin et al., 2024), suggesting complexity in the loneliness construct that warrants multidimensional measurement.

Educational and institutional contexts also influence loneliness trajectories. Adolescents in closed institutional settings report elevated ostracism and loneliness experiences (Boykina et al., 2024). Workplace loneliness literature, although focused on adults, parallels adolescent findings by demonstrating links between ostracism and silence or disengagement (ÖZİŞLİ, 2022). The psychosocial impact of perceived injustice and unforgiveness further illustrates relational dynamics relevant to exclusion processes (Boon & Brown, 2020). Post-pandemic transitions from loneliness to belonging have been documented, emphasizing the malleability of social connectedness (Carter & Shienko, 2023). Media narratives continue to underscore youth mental health vulnerabilities related to social isolation.

Despite this growing body of evidence, several gaps remain. First, much of the literature relies exclusively on subjective reports of exclusion, which may be influenced by cognitive biases or affective states. Second, cross-sectional designs predominate, limiting causal inference. Third, relatively few studies integrate objective digital trace data with validated loneliness measures. Although internet use has been linked to adolescent loneliness (Khararbakhova et al., 2021), nuanced computational analyses of actual interaction content are scarce. Fourth, research on parasocial relationships and gaming behaviors suggests alternative social engagement pathways that may mask or exacerbate loneliness (Risco & Mills, 2025). Finally, immigrant and marginalized groups exhibit unique belonging narratives that may require culturally sensitive assessment frameworks (Au et al., 2024).

Emerging profiles of loneliness and ostracism during adolescence highlight distinct subgroups with differential risk and protective factors (Kiuru et al., 2024). Family and teacher support function as moderators of ostracism–well-being associations (Tunkkari, 2025; Tunkkari et al., 2025). Longitudinal findings indicate that ostracism and loneliness may predict darker personality traits and maladaptive developmental trajectories (Pu & Gan, 2025). These patterns emphasize the importance of early identification and intervention.

In this context, machine learning–based detection of online social exclusion offers a novel methodological contribution. By combining natural language processing, behavioral analytics, and psychometric validation, researchers can move beyond purely subjective assessments toward hybrid models of psychosocial risk identification. Such integrative approaches may enhance ecological validity and permit early detection of at-risk adolescents in digital ecosystems. Furthermore, computational modeling aligns with contemporary interdisciplinary paradigms bridging psychology, data science, and public health.

The present study therefore seeks to address existing gaps by integrating supervised machine learning detection of online social exclusion with validated loneliness assessment among Mexican adolescents, examining both direct and

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indirect associations between objectively detected exclusionary patterns and subjective loneliness experiences.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, correlational design integrating computational text analytics with psychometric assessment to investigate the association between machine learning–detected online social exclusion and self-reported adolescent loneliness. The target population consisted of secondary school students enrolled in public and semi-public institutions in three metropolitan areas in central Mexico, including Mexico City, Puebla, and Toluca. A total of 742 adolescents participated in the study. After data screening for incomplete responses and low-quality digital text entries (e.g., repetitive characters, bot-like patterns, or texts shorter than 20 words), 718 cases were retained for final analysis. Participants ranged in age from 13 to 17 years ($M = 15.02$, $SD = 1.21$), with 52.4% identifying as female, 46.8% as male, and 0.8% as non-binary or preferring not to specify. Inclusion criteria required active use of at least one social media platform (e.g., Instagram, WhatsApp, TikTok, or Facebook) for a minimum of six months prior to participation and the provision of at least 10 recent anonymized social media interactions (messages or posts) for computational analysis. Adolescents with diagnosed severe psychiatric conditions that could impair informed assent were excluded based on school counseling records. Data collection was conducted during the 2025 academic year in supervised computer laboratory sessions to ensure standardized procedures and privacy protection.

2.2. Measures

Data collection integrated self-report psychometric instruments and digital behavioral data extraction. Loneliness was assessed using the Spanish-adapted version of the UCLA Loneliness Scale (Version 3), consisting of 20 items rated on a 4-point Likert scale ranging from 1 (never) to 4 (often). The instrument demonstrated strong internal consistency in the present sample (Cronbach's $\alpha = 0.91$). Online social exclusion experiences were measured in two complementary ways. First, participants completed the Online Social Exclusion Self-Report Scale, a 12-item instrument assessing perceived experiences of being ignored, excluded from group chats, left out of online events, or receiving minimal engagement (e.g., "being left on read," receiving no reactions). This scale showed acceptable reliability (Cronbach's $\alpha = 0.87$). Second, objective digital traces were collected through a secure, anonymized data upload system. Participants were instructed to export their last 30 days of direct message and comment interactions from their most frequently used platform. All identifying information, usernames, and images were automatically removed via a preprocessing script. The resulting textual dataset comprised 96,438 individual message entries. Additionally, metadata indicators such as response latency, frequency of initiated versus received interactions, number of ignored messages (no response within 48 hours), and reaction counts were extracted to construct behavioral indicators of exclusion. Socio-demographic variables including age, gender, socioeconomic status (based on parental education and household assets), and daily screen time were collected to serve as covariates.

2.3. Data Analysis

The machine learning component involved supervised classification to detect linguistic and interactional markers of online social exclusion within the anonymized text corpus. A subset of 8,000 message instances was randomly selected and manually coded by three trained bilingual (Spanish–English) psychologists for indicators of exclusionary communication (e.g., dismissive responses, non-reciprocal patterns, sarcastic rejection, coordinated ignoring). Inter-rater reliability was high (Cohen's $\kappa = 0.82$). This annotated dataset was divided into training (70%), validation (15%), and test (15%) subsets. Text preprocessing included tokenization, lemmatization, stop-word removal, and the generation of contextual embeddings using a pre-trained Spanish-language Bidirectional Encoder Representations from Transformers (BETO) model. Two classification algorithms were compared: a Support Vector Machine with a linear kernel and a fine-tuned transformer-based deep neural network. Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). The transformer-based model demonstrated superior performance (accuracy = 0.89, F1 = 0.87, AUC = 0.92) and was therefore selected to generate individual-level exclusion probability scores across the full dataset.

Following computation of exclusion probability indices, each participant received a composite Online Social Exclusion Index derived from weighted linguistic exclusion

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probability, proportion of unanswered messages, asymmetry in interaction initiation, and low engagement ratios. Descriptive statistics and assumption testing were conducted using SPSS Version 29, while machine learning modeling was performed in Python using TensorFlow and Scikit-learn libraries. Pearson correlation analyses examined bivariate associations between the exclusion index and loneliness scores. Hierarchical multiple regression analyses were conducted to determine whether machine learning–detected exclusion predicted loneliness after controlling for demographic variables and self-reported perceived exclusion. Multicollinearity diagnostics indicated acceptable tolerance and variance inflation factor levels. Additionally, a structural equation modeling approach using maximum likelihood estimation was employed in AMOS to test a latent model in which objective exclusion predicted loneliness both directly and indirectly through perceived exclusion. Model fit was evaluated using χ^2/df ratio, CFI, TLI, and RMSEA indices. All statistical tests were conducted with a significance level set at $p < 0.05$.

3. Findings and Results

Descriptive statistics were first computed to characterize the demographic composition of the sample and the distribution of key study variables. Table 1 presents the demographic characteristics of the 718 adolescents included in the final analyses, along with means and standard deviations for primary continuous variables, including loneliness, self-reported online social exclusion, machine learning–detected online exclusion probability, and average daily screen time.

Table 1

Demographic Characteristics and Descriptive Statistics of Study Variables (N = 718)

Variable	Category / Statistic	n	%	Mean	SD
Gender	Female	376	52.4	–	–
	Male	336	46.8	–	–
	Non-binary / Not specified	6	0.8	–	–
Age (years)	–	–	–	15.02	1.21
Socioeconomic Status	Low	198	27.6	–	–
	Middle	401	55.8	–	–
	High	119	16.6	–	–
Daily Screen Time (hours)	–	–	–	4.87	1.94
UCLA Loneliness Score	–	–	–	44.63	9.82
Self-Reported Online Exclusion	–	–	–	28.41	7.56
ML-Detected Online Exclusion Probability (0–1)	–	–	–	0.37	0.18
Unanswered Message Ratio	–	–	–	0.29	0.14

As shown in Table 1, the sample was relatively balanced in terms of gender distribution, with a slight predominance of female participants (52.4%). The average age was 15.02 years (SD = 1.21), indicating representation across early to middle adolescence. The majority of participants were classified within the middle socioeconomic status category (55.8%), followed by low (27.6%) and high (16.6%) socioeconomic groups. Adolescents reported an average daily screen time of 4.87 hours (SD = 1.94), reflecting substantial engagement with digital environments. The mean loneliness score (M = 44.63, SD = 9.82) fell within the moderate range based on normative cutoffs. Self-reported online exclusion scores also reflected moderate perceived exclusion (M = 28.41, SD = 7.56). The machine learning–detected exclusion probability demonstrated variability across participants (M = 0.37, SD = 0.18), indicating that approximately one-third of analyzed digital interactions were classified as containing exclusionary markers. The unanswered message ratio (M = 0.29, SD = 0.14) suggested that nearly 29% of outgoing messages did not receive responses within the 48-hour threshold.

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Table 2

Pearson Correlation Matrix Among Main Study Variables (N = 718)

Variable	1	2	3	4	5
1. Loneliness	1	–	–	–	–
2. Self-Reported Online Exclusion	0.62**	1	–	–	–
3. ML-Detected Online Exclusion	0.48**	0.54**	1	–	–
4. Unanswered Message Ratio	0.41**	0.46**	0.67**	1	–
5. Daily Screen Time	0.19**	0.22**	0.17**	0.14**	1

Note. **p < 0.01.

As shown in Table 2, loneliness demonstrated a strong positive correlation with self-reported online exclusion ($r = 0.62$, $p < 0.01$), indicating that adolescents who perceived higher levels of online exclusion reported significantly greater loneliness. Importantly, machine learning–detected online exclusion probability was also moderately and positively associated with loneliness ($r = 0.48$, $p < 0.01$), suggesting that objectively detected exclusionary linguistic and interactional markers corresponded with subjective emotional distress. The unanswered message ratio was significantly correlated with both ML-detected exclusion ($r = 0.67$, $p < 0.01$) and loneliness ($r = 0.41$, $p < 0.01$), reinforcing the behavioral relevance of digital non-responsiveness. Daily screen time showed weaker but statistically significant associations with loneliness ($r = 0.19$, $p < 0.01$), indicating that quantity of use alone was less strongly related to loneliness than qualitative exclusion experiences.

Table 3

Hierarchical Regression Predicting Adolescent Loneliness (N = 718)

Predictor	B	SE B	β	t	p
Step 1: Demographics					
Age	0.74	0.28	0.09	2.64	0.008
Gender (Female = 1)	1.82	0.67	0.10	2.72	0.007
Socioeconomic Status	-1.15	0.39	-0.11	-2.95	0.003
Daily Screen Time	0.58	0.21	0.09	2.76	0.006
Step 2: Self-Reported Online Exclusion					
Self-Reported Exclusion	0.73	0.05	0.57	14.60	<0.001
Step 3: ML-Detected Online Exclusion					
ML-Detected Exclusion	9.84	1.42	0.26	6.93	<0.001

Step 1 $R^2 = 0.07$
Step 2 $R^2 = 0.44$
Step 3 $R^2 = 0.50$

As shown in Table 3, demographic variables accounted for 7% of the variance in loneliness in Step 1 ($R^2 = 0.07$). The addition of self-reported online exclusion in Step 2 substantially increased explained variance to 44% ($\Delta R^2 = 0.37$, $p < 0.001$), confirming its strong predictive power. Critically, in Step 3, machine learning–detected online exclusion remained a statistically significant predictor ($\beta = 0.26$, $p < 0.001$) even after controlling for demographics and perceived exclusion, increasing total explained variance to 50% ($\Delta R^2 = 0.06$, $p < 0.001$). This finding indicates that computationally derived exclusion indicators provide incremental predictive validity beyond subjective perception measures.

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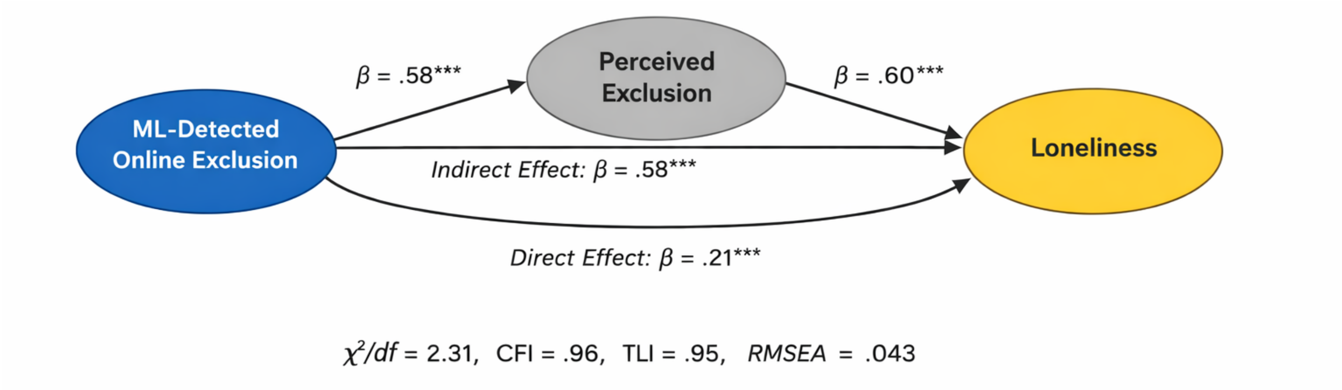
Figure 1

Structural Equation Model of ML-Detected Online Exclusion, Perceived Exclusion, and Loneliness



Structural equation modeling further examined direct and indirect pathways linking machine learning–detected exclusion to loneliness through perceived exclusion. The model demonstrated acceptable fit indices ($\chi^2/df = 2.31$, CFI = 0.96, TLI = 0.95, RMSEA = 0.043). Standardized path coefficients indicated that ML-detected exclusion significantly predicted perceived exclusion ($\beta = 0.58$, $p < 0.001$), and perceived exclusion significantly predicted loneliness ($\beta = 0.60$, $p < 0.001$). A direct path from ML-detected exclusion to loneliness remained significant ($\beta = 0.21$, $p < 0.001$), indicating partial mediation. Bootstrapping analyses confirmed that the indirect effect was statistically significant (95% CI [0.18, 0.29]). These results suggest that computationally identified exclusion patterns influence loneliness both by shaping adolescents' subjective perceptions of exclusion and through additional direct mechanisms, possibly reflecting cumulative emotional impacts of digital interaction asymmetry.

4. Discussion

The present study investigated whether machine learning–detected online social exclusion is associated with adolescent loneliness and whether computationally derived exclusion indicators provide incremental explanatory power beyond self-reported exclusion. The findings revealed three central patterns. First, machine learning–detected online exclusion probability was significantly and positively associated with loneliness. Second, this association remained statistically significant even after controlling for demographic variables and perceived exclusion, demonstrating incremental predictive validity. Third, structural equation modeling indicated that perceived exclusion partially mediated the association between computationally detected exclusion and loneliness. Together, these findings extend existing ostracism and loneliness research by integrating objective digital trace analysis with psychosocial assessment.

The positive association between machine learning–detected online exclusion and loneliness aligns with a substantial body of literature documenting the psychological impact of ostracism. Prior work has consistently shown that adolescents who experience social exclusion report higher levels of loneliness and internalizing symptoms (Arslan & Yıldırım, 2021; Boykina et al., 2024). The present findings replicate these associations within a digital context, suggesting that exclusionary linguistic patterns and response asymmetries captured algorithmically correspond meaningfully with adolescents' subjective emotional experiences. This supports theoretical propositions that ostracism threatens fundamental psychological needs, leading to loneliness as an affective outcome.

Importantly, the persistence of the association after controlling for self-reported exclusion underscores the added value of computational indicators. Previous research has relied heavily on self-report measures such as the Ostracism Experience Scale for Adolescents and Youth (Boykina et al., 2023). While psychometrically robust, such measures may be influenced by recall bias, attributional style, or mood congruency effects. The present findings demonstrate that objectively derived digital interaction markers—such as ignored messages and dismissive language—contribute unique explanatory variance. This complements evidence linking cyber-ostracism to adverse psychological outcomes (Ding et al., 2022) and cyber-victimization to loneliness (Heiman & Olenik-Shemesh, 2022). Our results suggest that algorithmically detected exclusion captures behavioral dynamics that adolescents may not fully articulate in self-reports.

The mediation findings provide additional theoretical insight. Machine learning–detected exclusion significantly predicted perceived exclusion, which in turn predicted loneliness, indicating partial mediation. This is consistent with developmental models positing that objective social experiences shape subjective appraisals, which then influence emotional outcomes. Profiles of loneliness and ostracism during adolescence demonstrate that perceived exclusion operates as a proximal determinant of well-being (Kiuru et al., 2024). Similarly, school-based research indicates that social outsiderhood predicts internalizing symptoms via psychological processes (Alanko et al., 2025). The present study extends these frameworks to digitally mediated contexts, suggesting that algorithmically identified exclusionary interactions influence loneliness both directly and through adolescents' perceptions.

The moderate-to-strong correlation between perceived exclusion and loneliness in this study echoes previous findings across diverse cultural settings. Comparative research among Indonesian and Malaysian students documented substantial loneliness variability associated with social connection differences (Pangestika et al., 2024). Thematic analyses of youth online forums revealed that adolescents interpret social disconnection in multifaceted ways, often integrating digital and offline experiences (Kaarakainen et al., 2025). The present findings are consistent with this literature, highlighting that online exclusion constitutes a meaningful dimension of adolescent social experience.

Our findings also contribute to the broader debate regarding social media's role in adolescent well-being. While digital platforms can facilitate belonging and identity exploration—particularly among marginalized youth (Charmaraman et al., 2024)—they may simultaneously amplify visibility of exclusion. Experimental evidence suggests that being ignored online may evoke stronger psychological threat than overt rejection (Lutz & Schneider, 2020). The machine learning detection of non-response patterns in this study aligns with that observation. Moreover, studies examining loneliness and social media addiction indicate that fear of missing out and excessive engagement may intensify feelings of disconnection (Tang et al., 2023). The present results suggest that not only quantity of use but qualitative interaction patterns—captured computationally—are critical determinants of loneliness.

The observed associations also resonate with research linking loneliness to broader psychosocial vulnerabilities. Loneliness has been associated with antisocial and prosocial online behaviors among narcissistic adolescents (Wang et al., 2023), as well as with maladaptive developmental trajectories including darker personality traits (Pu & Gan, 2025). Although the present study did not assess personality traits directly, the incremental predictive validity of computational exclusion suggests that repeated digital marginalization may contribute to broader psychosocial risk. Furthermore, longitudinal analyses indicate that loneliness and ostracism predict substance use and diminished psychological well-being (Tunkkari, 2025; Tunkkari et al., 2025). The identification of exclusion patterns through machine learning may therefore offer early indicators of downstream risk.

The cross-domain consistency of ostracism effects further supports the robustness of the findings. Workplace loneliness literature demonstrates that ostracism predicts silence and disengagement (ÖZİŞLİ, 2022). Similarly, cyberbullying research identifies loneliness as both predictor and outcome of online aggression (Olutola & Whitehouse, 2024; Razzaq, 2025). Variable-oriented analyses reveal that offline and online victimization overlap but retain distinct correlates (Burger & Bachmann, 2021). The present findings align with this multidimensional perspective by isolating exclusion—rather than overt aggression—as a salient predictor.

The absence of a full mediation effect suggests that computationally detected exclusion may influence loneliness through mechanisms beyond conscious appraisal. Need-threat theory posits that exclusion automatically activates affective responses. Physiological or attentional processes may be engaged prior to explicit perception. Research on tactile warmth reducing loneliness (Murphy, 2021) and awe fostering positive solitude (Jiang et al., 2023; Yin et al., 2024) indicates that emotional states may arise from subtle contextual cues. Thus, repeated exposure to subtle online ignoring—captured algorithmically—may generate affective consequences even in the absence of fully articulated perceived exclusion.

The present study also contributes methodologically by integrating computational modeling with psychosocial theory. Advances in machine learning applications within adolescent behavioral research highlight the feasibility of identifying psychosocial risk from digital traces (Pu & Gan, 2025). The integration of big data analytics addresses limitations of prior studies linking internet use to loneliness

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(Khararbakhova et al., 2021). By operationalizing exclusion probability through linguistic and interactional markers, this study advances measurement precision and ecological validity.

5. Conclusion

Collectively, the findings reinforce the centrality of belongingness in adolescent development. Systematic reviews demonstrate that social networks strongly predict subjective well-being (Webster et al., 2020). Experiences of social injustice and relational rupture predict psychological distress (Boon & Brown, 2020). Narratives of belonging among marginalized populations illustrate the protective function of relational inclusion (Au et al., 2024). Post-pandemic transitions from loneliness to belonging emphasize the dynamic nature of social connectedness (Carter & Shienko, 2023). In this context, early detection of exclusionary interaction patterns may provide a critical opportunity for intervention.

6. Limitations & Suggestions

Despite its contributions, this study has several limitations. The cross-sectional design precludes causal inference, and longitudinal designs would be necessary to establish temporal precedence between computationally detected exclusion and loneliness. Although machine learning enhanced objectivity, algorithmic classification remains probabilistic and may not capture nuanced contextual meanings such as playful teasing or culturally specific communication styles. The sample, while sizable and diverse within Mexico, limits generalizability to other cultural contexts. Additionally, the reliance on self-reported loneliness may introduce response bias. Future research incorporating multimethod assessments, including physiological or ecological momentary measures, would strengthen validity.

Future studies should adopt longitudinal and experimental designs to determine whether reductions in digitally detected exclusion lead to measurable decreases in loneliness. Cross-cultural comparisons would clarify whether algorithmic markers of exclusion generalize across linguistic and cultural contexts. Integration of personality traits, family support variables, and teacher support—identified as moderators in previous work—would deepen explanatory models. The incorporation of network centrality metrics and parasocial engagement indicators could further differentiate types of digital social involvement. Moreover, research exploring ethical frameworks and adolescent perceptions of algorithmic monitoring is essential to ensure responsible implementation.

Practically, the findings suggest that educational institutions and mental health professionals may benefit from incorporating digital literacy programs that address subtle forms of online exclusion. Schools could develop early-warning systems combining anonymized interaction analytics with psychosocial screening to identify at-risk students while preserving privacy. Interventions should strengthen social competence, self-esteem, and peer support networks to buffer against exclusion. Parental and teacher awareness initiatives can help adults recognize signs of digital ostracism. Ultimately, fostering inclusive online cultures and promoting meaningful peer engagement may reduce loneliness and enhance adolescent psychological well-being.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

References

Alanko, K., Söderberg, P., Lagerström, M., Laakso, M. J., & Junttila, N. (2025). The Association Between Social Outsiderhood and School Absence Is Mediated by Internalizing Symptoms. *School Mental Health*, *17*(3), 1041-1053. https://doi.org/10.1007/s12310-025-09793-8

Arslan, G., & Yıldırım, M. (2021). Psychological Maltreatment and Loneliness in Adolescents: Social Ostracism and Affective Experiences. *Psychological Reports*, *125*(6), 3028-3048. https://doi.org/10.1177/00332941211040430

Au, A., Hilario, C., Meherali, S., & Salma, J. (2024). Unveiling Social Belonging: Exploring the Narratives of Immigrant Muslim Older Women. *Health & Social Care in the Community*, *2024*(1). https://doi.org/10.1155/2024/5598247

Boon, S. D., & Brown, J. (2020). Associations Between Perceived Injustice, Unforgiveness, and Psychological Well-Being Among Ex-Communicants. *Journal of Social and Personal Relationships*, *37*(6), 1991-2011. https://doi.org/10.1177/0265407520914878

Boykina, E. E., Radchikov, A. S., Romanova, N. M., Pyatykh, G. A., & Kiselev, K. A. (2024). Teenager in Closed Institutions of the Educational System and the Federal Penitentiary Service of Russia: Ostracism Experience, Loneliness, Motives of Affiliation, Meaning and Life Orientations. *Bulletin of Psychological Practice in Education*, *20*(4), 106-118. https://doi.org/10.17759/bppe.2023200410

Boykina, E. E., Чиркина, P. B., Radchikov, A. S., Pyatykh, G. A., & Anisimova, E. V. (2023). Ostracism Experience Scale (Adolescent, Youth), OES-AY (In Russ.). *Psychology and Law*, *13*(4), 132-149. https://doi.org/10.17759/psylaw.2023130410

Bruneel, S. (2025). Exploring the Mediating Role of Social Media and Gaming in the Relationship Between Adolescents' Feelings of Loneliness, Ostracism and Internalizing and Externalizing Symptoms. https://doi.org/10.21203/rs.3.rs-7944252/v1

Burger, C., & Bachmann, L. (2021). Perpetration and Victimization in Offline and Cyber Contexts: A Variable- And Person-Oriented Examination of Associations and Differences Regarding Domain-Specific Self-Esteem and School Adjustment. *International journal of environmental research and public health*, *18*(19), 10429. https://doi.org/10.3390/ijerph181910429

Carter, A. D., & Shienko, L. (2023). From Loneliness to Belonging Post Pandemic. 209-232. https://doi.org/10.4018/978-1-6684-5190-8.ch011

Charmaraman, L., Zhang, A., Wang, K., & Chen, B. (2024). Sexual Minorities and Loneliness: Exploring Sexuality Through Social Media and Gender–Sexuality Alliance (GSA) Supports. *International journal of environmental research and public health*, *21*(3), 300. https://doi.org/10.3390/ijerph21030300

Ding, H., Zhu, L., Hua, W., Geng, J., Huang, F., & Lei, L. (2022). The Relationship Between Cyber-Ostracism and Adolescents' Non-Suicidal Self-Injury: Mediating Roles of Depression and Experiential Avoidance. *International journal of environmental research and public health*, *19*(19), 12236. https://doi.org/10.3390/ijerph191912236

Dreslin, B., & Hedrick, M. E. (2023). Finding Friends: The Role of Loneliness on the Formation of Online Friendships Among Adolescents. *Journal of Student Research*, *12*(3). https://doi.org/10.47611/jsrhs.v12i3.5087

Heiman, T., & Olenik-Shemesh, D. (2022). Cyber-Victimization Experience Among Higher Education Students: Effects of Social Support, Loneliness, and Self-Efficacy. *International journal of environmental research and public health*, *19*(12), 7395. https://doi.org/10.3390/ijerph19127395

Jiang, T., Yin, Y., Yuan, W., Hao, C., Du, Y., Xu, Z., & Hicks, J. A. (2023). Alone but Not Lonely: Awe Fosters Positive Attitudes Toward Solitude. https://doi.org/10.21203/rs.3.rs-3261143/v1

Kaarakainen, S.-S., Helenius, J., & Laakso, M. (2025). Exploring Loneliness Among Young People: Thematic Analysis of Loneliness Experiences on Finnish YouthNet Discussion Forum. *Youth & Society*, *57*(5), 852-877. https://doi.org/10.1177/0044118x241313475

Khararbakhova, M. A., Musatova, O. A., & Shpagina, E. M. (2021). Internet and Loneliness of Adolescents. *Psychology and Law*, *11*(4), 2-13. https://doi.org/10.17759/psylaw.2021110401

Kiran, P. M., & Thiruchelvi, A. (2020). A Study on Role of Big 5 Personality Traits on Social Ostracism. *Shanlax International Journal of Management*, *8*(2), 103-107. https://doi.org/10.34293/management.v8i2.3430

Kiuru, N., Salmela-Aro, K., Laursen, B., Vasalampi, K., Beattie, M., Tunkkari, M., & Junttila, N. (2024). Profiles of Loneliness and Ostracism During Adolescence: Consequences, Antecedents, and Protective Factors. *Child Psychiatry & Human Development*, *56*(6), 1637-1657. https://doi.org/10.1007/s10578-024-01664-8

Lutz, S., & Schneider, F. M. (2020). Is Receiving Dislikes in Social Media Still Better Than Being Ignored? The Effects of Ostracism and Rejection on Need Threat and Coping Responses Online. https://doi.org/10.31234/osf.io/328j4

Miao, Y., Jasim, N., Guha, C., Sluiter, A., Owen, K., Yudianto, B., Lim, M. H., Smith, B. J., & Manera, K. (2024). Experiences of Loneliness and Social Isolation Among Young People With Chronic Physical Conditions: A Thematic Synthesis of Qualitative Studies. *Journal of adolescence*, *97*(3), 593-608. https://doi.org/10.1002/jad.12445

Murphy, P. N. (2021). Tactile Warmth Reduces Loneliness, but Visual Warmth Does Not. *Individual Differences Research*, *19*. https://doi.org/10.65030/idr.19004

Olutola, B., & Whitehouse, C. (2024). Cyberbullying Among School Going Adolescents. What Are the Associated Factors? *Jayps*, *5*(11), 132-143. https://doi.org/10.61838/kman.jayps.5.11.16

ÖZİŞLİ, Ö. (2022). The Effect of Workplace Ostracism on Organizational Silence and Workplace Loneliness a Study on Healthcare Workers. *International Journal of Health Services Research and Policy*, *7*(3), 300-308. https://doi.org/10.33457/ijhsrp.1131522

Pangestika, V. W., Jati, S., & a, V. N. (2024). Comparative Study of Loneliness in Indonesian and Malaysian Students. *Psikoislamedia Jurnal Psikologi*, *9*(1), 16-26. https://doi.org/10.22373/psikoislamedia.v9i1.22743

Pu, J., & Gan, X. (2025). The Potential Roles of Social Ostracism and Loneliness in the Development of Dark Triad Traits in Adolescents: A Longitudinal Study. *Journal of personality*, *94*(1), 81-93. https://doi.org/10.1111/jopy.13018

Razzaq, A. (2025). Cyberbullying, Loneliness and Use of Social Media Among College Students. *Contemporary Journal of Social Science Review*, *3*(4), 158-166. https://doi.org/10.63878/cjssr.v3i4.1729

Risco, S., & Mills, D. J. (2025). Interpersonal and Gaming Behaviors: Contrasting Players With and Without Parasocial Relationships With Fictional Characters. https://doi.org/10.31234/osf.io/9wfsd_v1

Sakız, H., Mert, A., & Sarıçam, H. (2020). Self-Esteem and Perceived Social Competence Protect Adolescent Students Against Ostracism and Loneliness. *Journal of Psychologists* *and Counsellors in Schools*, *31*(1), 94-109. https://doi.org/10.1017/jgc.2020.25

Sluiter, A., Cazzolli, R., Jauré, A., Scholes-Robertson, N., Craig, J. C., Johnson, D. W., González, A. M., Sautenet, B., Smith, B. J., & Manera, K. (2024). Experiences of Social Isolation and Loneliness in Chronic Kidney Disease. *Clinical Journal of the American Society of Nephrology*, *19*(11), 1405-1416. https://doi.org/10.2215/cjn.0000000000000529

Stavrova, O., Ren, D., & Pronk, T. (2021). Low Self-Control: A Hidden Cause of Loneliness? *Personality and Social Psychology Bulletin*, *48*(3), 347-362. https://doi.org/10.1177/01461672211007228

Tang, T.-C., Chi, L. C., & Tang, E. (2023). Office Islands: Exploring the Uncharted Waters of Workplace Loneliness, Social Media Addiction, and the Fear of Missing Out. *Current Psychology*, *43*(17), 15160-15175. https://doi.org/10.1007/s12144-023-05445-9

Tunkkari, M. (2025). Adolescents' Loneliness and Ostracism: Teacher and Family Support as Protective Factors. *European journal of public health*, *35*(Supplement_4). https://doi.org/10.1093/eurpub/ckaf161.637

Tunkkari, M., Kiuru, N., Junttila, N., Paakkari, L., & Lyyra, N. (2025). The Role of Loneliness and Ostracism in Adolescents' Psychological Well-Being and Substance Use: Family and Teacher Support as Moderators. *Journal of adolescence*, *98*(2), 371-382. https://doi.org/10.1002/jad.70067

Wang, Y., Hawk, S. T., Wong, N., & Zhang, Y. (2023). Lonely, Impulsive, and Seeking Attention: Predictors of Narcissistic Adolescents' Antisocial and Prosocial Behaviors on Social Media. *International Journal of Behavioral Development*, *47*(6), 540-547. https://doi.org/10.1177/01650254231198034

Webster, D., Dunne, L., & Hunter, R. F. (2020). Association Between Social Networks and Subjective Well-Being in Adolescents: A Systematic Review. *Youth & Society*, *53*(2), 175-210. https://doi.org/10.1177/0044118x20919589

Yin, Y., Yuan, W., Hao, C., Du, Y., Xu, Z., Hicks, J. A., & Jiang, T. (2024). Awe Fosters Positive Attitudes Toward Solitude. *Nature Mental Health*, *2*(6), 717-727. https://doi.org/10.1038/s44220-024-00244-y