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The Development of Probability for Risk Assessment on Cyber Bullying Experience: A Case Study on Secondary School Students

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ABSTRACT

The rapid expansion of information and communication technology (ICT) has transformed how adolescents interact and learn but has also heightened the risk of cyberbullying among Malaysian secondary school students. This study develops and validates a probability-based risk assessment model to examine the impact of cyberbullying on students' academic performance. Using an action research design, data were collected through expert input from school counsellors and surveys administered to 258 secondary students in Kota Setar, Kedah. Six key dimensions were identified: victimization experience, social media use, guardian involvement, personality, lack of internet literacy, and peer influence. These dimensions were integrated into a Cyberbullying Probability Flowchart (CbPF) and a risk matrix to measure severity levels. Findings indicate that students who spend more than three hours daily on social media are at significantly higher risk of cyberbullying, resulting in lower academic engagement, weaker time management, and diminished learning motivation. Gender and place of residence also emerged as significant factors, with female students and those living with parents reporting greater emotional distress and academic disruption. Common forms of cyberbullying included online harassment, social exclusion, rumours spreading, and the non-consensual sharing of personal content. Theoretically, this research integrates digital behaviour, psychosocial vulnerability, and academic outcomes into a comprehensive risk assessment framework. Practically, it provides actionable insights for educators, parents, and policymakers to design early intervention and targeted prevention strategies. Methodologically, it introduces a data-driven, expert-validated probabilistic model that can be replicated to assess cyber-related risks in educational contexts. Overall, the study underscores the urgent need for collaborative preventive measures to safeguard students' emotional well-being and academic success in an increasingly digital society.

Keywords:
Cyberbullying; Risk assessment; Academic performance; Secondary education; Social media; Emotional well-being; Malaysia

1. Introduction

The rapid advancement of electronic technology and the global expansion of social media have generated many positive outcomes, particularly in communication, learning, and information sharing. However, these developments also present serious challenges, especially for secondary

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school students. With internet accessibility becoming increasingly widespread, adolescents now rely heavily on social media platforms as primary channels for interaction. While these platforms provide opportunities for connectivity and self-expression, they simultaneously expose young users to risks that may disrupt their emotional stability, social development, and academic progress. At a formative stage of psychological and social growth, adolescents are highly vulnerable to the adverse consequences of excessive and unsupervised online engagement. Issues such as cyberbullying, online harassment, invasion of privacy, and peer pressure in digital spaces have become common, often leading to emotional distress, psychological instability, and disengagement from learning. These risks undermine not only academic performance but also students' personal growth, resilience, and overall well-being. Recent national statistics highlight the urgency of this issue. The Malaysia Computer Emergency Response Team (MyCERT) recorded 8,399 cyberbullying complaints between January and November 2024 averaging 27 cases per day marking a significant increase compared to previous years. Over a three-year span (2022–2024), nearly 9,500 cases were reported, indicating that cyberbullying is not only escalating but also becoming one of the most pressing digital threats faced by Malaysian adolescents. Facebook, WhatsApp, Instagram, TikTok, and Twitter were identified as the most common platforms associated with reported cases, with adolescents aged 13 to 17 representing the most affected group. This age group is characterized by intense social media engagement, heightened peer dependence, and ongoing identity formation factors that collectively amplify susceptibility to online victimization.

These statistics reflect a troubling reality: cyberbullying is no longer an isolated issue but a widespread phenomenon requiring urgent attention. It calls for collective responses that include strengthening digital literacy, enforcing progressive cyber laws, and developing empathetic interventions that address the vulnerabilities of young people in online environments. Within the Malaysian education system, the growing prevalence of cyberbullying underscores the need for systematic approaches that protect students' psychosocial well-being while also supporting their academic achievement.

2. Methodology

The development of the Impact Equation (EXPERT) is designed to integrate expert judgment into the quantitative assessment of cyberbullying risk factors. The formula is expressed as:

$$\mathrm{Pr} = \sum_{1}^{f} \alpha_f \ \omega_f \tag{1}$$

This probability consists of α_f (experts) weightage while ω_f (students score). Which includes factors B1 to B6 to study the probability that it will happen to high school students. Furthermore, this formula method can also be used to calculate risk based on the scale of the risk matrix table.

Where:

- *Pr* represents the overall probability score or the aggregated measure of cyberbullying risk based on expert evaluations.
- f denotes the factor index, representing each of the identified risk factors contributing to cyberbullying.

- αf refers to the assigned score or rating for factor f based on expert assessment, typically derived from empirical data, interviews, or structured questionnaires.

- ωf denotes the weightage of factor f which represents its relative importance as determined by experts (as discussed in the Weightage of Experts section).

This formulation operates as a weighted summation, where each factor's score is multiplied by its corresponding expert-assigned weightage. The sum of these weighted values yields an aggregated probability score, which serves as a quantitative indicator of the likelihood and potential severity of cyberbullying within a given school context.

The use of this weighted approach ensures that the probability computation reflects both the empirical presence of each factor αf and its relative significance in the real-world context ωf as determined by expert judgment. This methodology provides a more robust and context-sensitive risk estimation compared to unweight models, which may treat all factors as having equal influence.

Furthermore, integrating expert-derived weightages into the impact equation enhances the construct validity of the model, as it accounts for nuanced, experience-based knowledge that may not be fully captured through raw statistical data alone. The equation therefore serves as a critical step in bridging theoretical risk constructs with practical, evidence-based intervention planning.
Where:

f : Number of factors f

α_f : Weightage for factor f

ω_f : Student score for factor f

$\alpha_f = \frac{AVS_f}{AVS\ T}$

Where:
AVS_f : Expert average score for factor f

AVS_T : Total Experts' average score for all factors.

2.1 Calculation of Weightage for Expert

To determine the probability, it is essential to obtain the weightage αf for each contributing factor. Referring to Equation 1 above, the value of αf for each factor can be derived by following the procedural steps outlined below.

2.1.1 Step One: Calculation of Total Score

The first stage involves calculating the total score assigned by the experts who participated in the study. Six predetermined factors are evaluated, with each factor assigned a total score denoted as TS1, TS2, TS3, TS4, TS5, and TS6. The total score for each factor is obtained by summing the scores given by all experts for the questions associated with that factor.

For instance, Table 10 presents the expert scores for Factor 2: Social Media Factors. Each expert assigns a numerical rating to several related questions (e.g., Q1, Q2, and Q3). These individual question scores are then aggregated to generate a total score for each expert.

Example Calculation:
Expert 1: Q1 = 4, Q2 = 2… Total Score = 16
Expert 2: Q1 = 3, Q2 = 5… Total Score = 15
Expert 3: Q1 = 1, Q2 = 2… Total Score = 5

This procedure is repeated systematically for all six factors to produce a complete set of total scores. These total scores serve as the foundational input for subsequent probability computation and risk assessment analyses.

Table 1
Experts' scores for each question in Factor B2, which is Social Media Factors

Ex	Q1	Q2	Q3	Q4	Q5	TOTAL
Expert 1	4	2	4	3	3	16
Expert 2	3	3	3	3	3	15
Expert 3	1	1	1	1	1	5
Expert 4	2	2	3	3	2	12
Expert 5	2	1	3	2	2	10
Expert 6	3	2	3	3	3	14
Expert 7	1	0	2	2	2	7
Expert 8	3	2	3	3	2	13
Expert 9	2	1	3	4	3	13
Expert 10	1	1	2	1	2	7
	22	**15**	**27**	**25**	**23**	**112**

This interpretation not only strengthens the quantitative foundation of the risk assessment model but also reinforces the validity of the instrument through the involvement of experienced practitioners in counselling and secondary school education.

To calculate each expert based on questions, which are Q1 to Q5. For example,

E1 = Q1 (4) + Q2 (2) + Q3 (4) + Q4 (3) + Q5 (3) = TS 16

The same process is used for all the Experts.

Lastly, in this step, we sum up the totals to get the total score for the experts for factor B2, which is 112. From a methodological standpoint, the dataset will be utilized to:

Calculate the Average Score (AVS) for each question across all experts. Determine the Weightage (α) of Factor B2 for integration into the overall risk index calculation.

Assess Expert Agreement by analysing the range and variance of scores provided.

Table 2
Calculation of Total Score for all factors

Factor	Title	Total Score
B1	Experience Victimization	53
B2	Social media	112
B3	Guardians	144
B4	Personality	90
B5	Lack Of Knowledge of Internet	122
B6	Usage Peers	44

The table presents the total scores obtained for six key factors identified through expert evaluation in the development of the cyberbullying risk assessment model. Each factor represents a specific dimension influencing students' exposure to cyberbullying risk, where a higher score reflects the experts' perception of its relative significance in contributing to overall vulnerability.

The analysis indicates that Factor B3: Guardians recorded the highest total score (144), suggesting that the influence of guardians or individuals responsible for students is perceived as the most critical element in determining susceptibility to cyberbullying. This is followed by B5: Lack of Knowledge of Internet Usage (122) and B2: Social Media (112), both of which highlight the importance of digital literacy and social media engagement as substantial predictors of cyberbullying risk.

B4: Personality scored 90, indicating that personal attributes such as self-control, confidence, and social tendencies also play a considerable role in shaping students' risk levels. B1: Experience Victimization (53) falls within the moderate range, while B6: Peers (44) recorded the lowest score, implying that peer influence is perceived as the least dominant dimension compared to other factors in the context of this study.

From a methodological standpoint, these score variations will be utilized in the calculation of weightage for each factor within the risk assessment model. The weightage values allow the model to priorities analytical emphasis on factors with greater impact, thereby enhancing the accuracy of risk prediction and the effectiveness of targeted intervention strategies.

Overall, the findings underscore the pivotal roles of guardian involvement, internet literacy, and social media use as the primary areas of focus in preventive and mitigation efforts to address cyberbullying risks among secondary school students.

2.1.2 Step Two: Calculation of Expert Average Score (AVS)

In this step, we need to calculate the expert average score (AVS) for all the factors. To calculate these AVS, we need the maximum score for each factor. Table 3 below shows how to calculate the maximum score:

Table 3
Calculation of the maximum score

Factor	Num Of Questions	Maximum Score for Each Question	Number Of Experts	Maximum Score
B1	7	4	10	280
B2	4	4	10	160
B3	7	4	10	280
B4	5	4	10	200
B5	5	4	10	200
B6	4	4	10	160

The table outlines the structural scoring framework applied to six primary factors within the cyberbullying risk assessment model. Each factor is associated with a specific number of questions, a fixed maximum score per question, and the number of experts contributing to the evaluation. These parameters collectively determine the maximum attainable score for each factor, which serves as a benchmark against which the actual expert scores are compared.

The data reveal that Factor B1: Experience Victimization and Factor B3: Guardians each hold the highest maximum score of 280 points, reflecting their broader scope of assessment through seven questions evaluated by ten experts. This expansive coverage indicates the multidimensional nature of these factors, capturing a more comprehensive range of risk indicators.

Factor B4: Personality and Factor B5: Lack of Knowledge of Internet Usage each have a maximum possible score of 200 points, derived from five assessment questions. This score allocation suggests a moderately broad investigative scope, enabling a balanced yet focused evaluation of these dimensions in relation to cyberbullying vulnerability.

At the lower end, Factor B2: social media and Factor B6: Peers both present a maximum possible score of 160 points, each assessed through four questions. While these factors are narrower in scope compared to B1 and B3, their inclusion reflects the model's recognition of targeted behavioural and environmental influences on students' risk exposure. From a methodological perspective, the variation in maximum scores across factors underscores the model's strategic weighting design, ensuring that dimensions with wider or more complex constructs (e.g., B1 and B3) are given greater evaluative breadth. Conversely, more specific factors (e.g., B2 and B6) are assigned fewer but focused indicators to maintain analytical precision without overrepresentation.

This scoring architecture not only facilitates a balanced risk quantification process but also enhances the validity of inter-factor comparisons, enabling the identification of priority areas for intervention and policy development.

These maximum scores are calculated by multiplying the number of questions by the maximum score for each question by the number of experts. For example, for factor B1, we multiply as follows:

Max Score for factor B1 = number of questions in B1 X max score for each question X number of experts.

Where;
= 7 X 4 X 10
= 280

The same processes are used for all the factors.

Next, we divide the total score for each factor (which is shown in Step 1) by the corresponding maximum score to get the average score (AVS). Table 4 below shows the total score, max score, and average score (AVS) for each factor.

Table 4
The total score, max score, and average score (AVS) for each factor

Factor	Total Score	Max Score	Average Score (AVS)
B1	53	280	0.18928
B2	112	160	0.70000
B3	144	280	0.51428
B4	90	200	0.45000
B5	122	200	0.61000
B6	44	160	0.27500

The table compares the actual scores obtained for each risk factor with their corresponding maximum possible scores, resulting in the Average Score (AVS) for each dimension. AVS serves as a quantitative indicator of the relative importance or influence of a factor, as perceived by the panel of experts. A higher AVS value denotes that the factor is considered more significant in contributing to students' vulnerability to cyberbullying.

The analysis reveals that Factor B2: social media recorded the highest AVS (0.70000), indicating that experts view social media usage as the most dominant factor increasing students' susceptibility to cyberbullying. This is followed by B5: Lack of Knowledge of Internet Usage (0.61000) and B3: Guardians (0.51428), underscoring the crucial roles of digital literacy and guardian involvement in mitigating cyber-related risks.

Factor B4: Personality achieved a moderate AVS (0.45000), suggesting that personality traits such as self-control, confidence, and social tendencies exert a notable but less prominent influence compared to technology-related or support- based factors. B6: Peers (0.27500) and B1: Experience Victimization (0.18928) recorded the lowest AVS values, indicating that, while relevant, these factors are perceived as less critical in the overall risk hierarchy within the context of this model.

From a methodological perspective, AVS forms the basis for calculating the weightage assigned to each factor in the risk assessment model. This approach ensures that the model not only accounts for the presence of risk factors but also applies proportional emphasis to those with the greatest perceived impact on students' safety and academic engagement.

Overall, the findings highlight that technology-related dimensions and digital literacy (B2 and B5), alongside guardian support (B3), and should be prioritized in preventive interventions, whereas personal characteristics and prior victimization experiences may require more tailored support strategies.

To calculate the AVS as below, For example,
Total score 53 = **AVS 0.18928**
Max score 280

The same process is done for all the factors.

2.1.3 Step Three: Calculation of Weightage, αf

Firstly, we need to sum up all the expert average scores for all the factors that we get in Table 5 (Step 2). Table 5 below shows the summation of all the average scores.

Table 5
The summation of all the average scores

Factor	Average Score (AVS)
B1	0.18928
B2	0.70000
B3	0.51428
B4	0.45000
B5	0.61000
B6	0.27500
Total Expert Average (AVS_{T})	**2.73856**

To calculate the summation of all the average scores.

For example,

B1 (0.18928) + B2 (0.70000) + B3 (0.51428) + B4 (0.45000) + B5 (0.61000) + B6 (0.27500)
Sum of AVS = **2.73856**

The same process is done for all the factors.

Next, we need to calculate the weightage. Weightage for each factor is calculated by dividing the average score, AVSf, by the total expert average score, AVST.

Table 6
The weightage for each factor

Factor	Weightage
B1	0.0728
B2	0.2155
B3	0.1979
B4	0.1732
B5	0.2347
B6	0.1058
	1

To calculate the weightage as below,

$$\frac{\text{AVS of factor B1}}{\text{Total Expert Average (AVST)}} = \frac{\mathbf{0.18928}}{\mathbf{2.73856}} = \mathbf{0.06911}$$

The same process is done for all the factors.

Lastly, with the weightage obtained above, we can use Equation 2.

$$Pr = \alpha 1\ \omega_1 + \alpha 2\ \omega_2 + \alpha 3\ \omega_3 + \alpha 4\ \omega_f + \alpha f\ \omega_f + \alpha f\ \omega_f$$

$$Pr = 0.0691 w 1 + 0.255609 \omega_2 + 0.187792 \omega_3 + 0.16432\ \omega_4 + 0.222745 \omega_5 + 0.100418 \omega_6 \quad (2)$$

3. Results

The results are structured progressively, beginning with the probability distribution of risk factors across Forms (4.1), followed by the conversion of these probabilities into risk levels (4.2). The chapter then moves towards demographic comparisons, specifically gender (4.3), guardian background (4.4), and online duration (4.5). Each subsection integrates the empirical data with insights from contemporary literature, allowing for a deeper understanding of how digital exposure, literacy, and social context shape students' vulnerability. The chapter concludes with a summary of results (4.6), highlighting key implications for digital education and policy interventions.

3.1 Probability of Risk Factors across Forms

The probability analysis demonstrates that two factors B2: Social Media Influence and B5: Lack of Internet Knowledge remain consistently dominant across all Forms. Specifically, B2 probability ranges between 0.9733 (Form 1) and 0.9873 (Form 3), while B5 spans from 0.8864 (Form 1) to 0.9858 (Form 4). The narrow margins suggest a persistent and systemic vulnerability among students, regardless of grade level. By contrast, other factors such as B1: Victimization (0.6457–0.7021) and B6: Peer Influence (0.6034–0.6812) show moderate probabilities, while B3: Guardian and B4: Personality fluctuate in the mid-range, indicating less dominance in shaping risk perception.

This finding aligns with Uhls et al. (2022), who reported that adolescents' reliance on social media as their primary communication channel has intensified, simultaneously exposing them to cyberbullying, emotional strain, and poor time management. Moreover, Livingstone et al. (2023) observed persistent digital literacy gaps among European students, which mirror the high probability of B5 in this study. Similarly, Malaysian research by Aziz et al. (2021) confirmed that limited parental digital competency exacerbates students' risk of misinformation and online harm.

3.2 Risk Level Analysis

When probabilities are converted into risk levels, sharper distinctions emerge. B2: Social media attains a Very High-risk level at 0.2412, while B5: Lack of Internet Knowledge follows closely at High with 0.2223. Other factors remain moderate: B3: Guardian at 0.1153, B4: Personality at 0.1405, whereas B1: victimization (0.0892) and B6: Peer Influence (0.1011) are categorized as Low. This indicates that students' risks are less rooted in direct victimization but more embedded in the structural ecosystem of online interaction and digital literacy.

According to Keles, McCrae, and Grealish (2020) found that excessive exposure to social media significantly increases depressive symptoms, anxiety, and stress among adolescents, particularly when combined with weak digital competencies. Similarly, Kowalski et al. (2021) highlighted that cyberbullying risk often arises not from individual conflict but from the broader architecture of online platforms, amplifying the relevance of this study's findings. These insights reinforce the argument that preventive strategies should priorities digital education and critical literacy training rather than focusing solely on protective monitoring.

3.3 Gender-Based Risk

The gender-based analysis reveals a nuanced pattern. Female students demonstrate higher weight values (ω) across most factors, such as B2: social media (0.9871 vs. 0.9723 in males) and B4: Personality (0.9035 vs. 0.8762 in males). Interestingly, male students surpass females in B5: Lack of Knowledge (0.9467 vs. 0.8925), indicating weaker digital literacy among boys.

Despite these variations, the overall total risk score is equal across genders, suggesting that vulnerabilities are multidimensional and distributed differently rather than disproportionately heavier on one group.

This resonates with Anderson and Jiang (2018), who reported that teenage girls often express greater emotional distress linked to social media, especially around self-image and peer comparisons. Conversely, boys tend to underreport risks, approaching digital platforms with a recreational lens but lacking the critical literacy to mitigate hidden dangers (Lee & Shin, 2022). Local studies, such as Hashim et al. (2021), confirmed that Malaysian female students more frequently perceive cyberbullying as emotionally harmful, while male students underestimate its long-term consequences, despite being equally exposed.

3.4 Guardian-Based Risk

Guardian analysis indicates that students living with parents record the highest probabilities for B2 (0.9463) and B5 (0.9640) compared to hostel residents (B2: 0.8721, B5: 0.9013) or those under alternative guardianship (B2: 0.8910, B5: 0.9234). This paradox implies that co-residence with parents does not necessarily reduce risk exposure. Instead, limited parental digital literacy and lenient monitoring practices may unintentionally increase risk.

According to Chassiakos et al. (2021) observed that middle-aged parents frequently struggle to establish effective screen-time regulations, echoing the gaps identified here. Further, Lim (2022) highlighted that in Asian contexts, parental authority is often assumed to guarantee digital safety; however, without proper literacy, this authority is undermined. Thus, the results suggest that guardian presence alone is insufficient active engagement and co-learning in digital spaces are crucial to reducing adolescent vulnerability.

3.5 Online Duration and Risk

Duration of online activity reveals the most striking vulnerability. Students spending more than 3 hours daily online show near-maximal probabilities: B2: 0.9978 and B5: 0.9994. By contrast, those online for less than 2 hours maintain significantly lower probabilities (B2: 0.8756, B5: 0.9017). This finding underscores the paradox of online immersion: greater exposure does not equate to better digital competence, but instead increases susceptibility.

Twenge et al. (2023) found that prolonged social media use correlates strongly with depressive symptoms, disrupted sleep patterns, and academic decline. Similarly, Sampasa-Kanyinga and Lewis (2019) reported that heavy-users are more vulnerable to loneliness and cyber victimization. In Southeast Asia, research by Rahim & Pawanchik (2021) indicated that Malaysian adolescents exceeding 3 hours online daily face heightened risks of online harassment, confirming the contextual relevance of this study's data.

3.6 Recaption of the Research

This study set out to examine the risks of cyberbullying and its influence on students' academic performance by developing and testing a probability-based risk assessment model. The research was motivated by the increasing prevalence of cyberbullying among secondary school students in Kedah, where digital connectivity and social media use are part of daily life.

The central aim of the study was to construct a comprehensive model that could quantify and categories the risks of cyberbullying in a school context. To achieve this aim, four objectives were pursued: (i) to quantify the risks of cyberbullying on academic performance, (ii) to develop a model for measuring cyberbullying risks, (iii) to test the model on real cases involving secondary students, and (iv) to validate the model through sensitivity analysis.

The research design combined expert evaluation from school counsellors with survey data from students, resulting in the identification of six key factors that contribute to cyberbullying risk: victimization experiences, social media usage, peer influence, personality, guardianship, and lack of knowledge of internet use. These factors were systematically weighted and integrated into a

Cyberbullying Probability Flowchart (CbPF) and a risk matrix, enabling both probability and impact to be quantified.

The findings showed that demographic and behavioral variables play a significant role in shaping cyberbullying risks. For example, female students and those living in hostels were found to be more vulnerable, while students who spent more than three hours daily on social media exhibited higher risk scores. These results confirm that cyberbullying not only affects emotional well-being but also undermines academic engagement and performance.

By developing and validating this model, the study makes important contributions to theory, methodology, and practice. It expands theoretical understanding by linking cyberbullying with risk management principles, introduces a methodological innovation through the quantification of probability and impact, and provides practical tools for educators, parents, and policymakers to address cyberbullying more effectively.

4. Discussion Of Study Findings

This section discusses the findings of the study in relation to the research objectives. Each objective is examined based on the evidence presented in Chapter Four and is interpreted in the context of existing literature and theoretical perspectives.

Objective 1: To quantify the risks of cyberbullying on secondary students' academic performance

The findings demonstrated that cyberbullying has a measurable impact on students' academic engagement and performance. Through the risk quantification model, six key factors were identified, including victimization experiences, social media usage, peer influences, personality, guardianship, and lack of knowledge on internet usage. Among these, peer factors and social media- related behaviors were the most dominant contributors to overall risk.

This result supports previous studies (Tan & Abdullah, 2025; Cedeño et al., 2024) which revealed that excessive exposure to social media and online harassment directly interferes with students' concentration, motivation, and study time management. The probability scores derived from the model confirm that students who spend more than three hours daily on social media are at higher risk of being cyberbullied, which correlates with reduced academic effort and lower engagement in classroom activities.

Thus, the quantification approach not only validates the academic impact of cyberbullying but also provides empirical evidence that risk can be measured systematically rather than being viewed as a purely subjective phenomenon.

Objective 2: To develop a model for measuring the risks of cyberbullying in students at school

The study successfully developed a Cyberbullying Probability Flowchart (CbPF) combined with a weighted scoring system to categories students into different levels of risk. This model integrates demographic information (gender, residence, and school form) with behavioral factors such as time spent on social media.

The results showed that female students and those living in parents were more vulnerable to cyberbullying risks compared to their peers. This aligns with Yusof et al. (2022), who found that girls tend to experience more relational aggression such as exclusion and rumor-spreading, while male students are more often perpetrators. By embedding demographic and behavioral factors into the risk assessment model, the study extends the scope of existing frameworks which were previously more generic (Smith & Steffgen, 2022).

Hence, the proposed model contributes both theoretically and practically by offering a school-based tool that counsellors and educators can apply to identify students at heightened risk.

Objective 3: To test the developed model on selected secondary students as a case study

The model was tested on a sample of 258 students across different forms (Form 1 to Form 5). The results indicated that risk distribution varied significantly by age group. For instance, Form 1 students exhibited higher risk levels compared to Form 2 and form 3, suggesting that vulnerability increases with age and prolonged exposure to social media.

This pattern reflects developmental perspectives which argue that adolescents between 13 and 17 years are at a critical stage of identity formation and thus more sensitive to peer influence (Heiman & Olenik-Shemesh, 2018). The model's ability to capture this variation strengthens its validity and demonstrates its applicability in real educational contexts.

Furthermore, comparisons between individual students (Student 1 and Student 2 in Chapter Four) revealed that differences in online behavior, particularly time spent on digital platforms, resulted in markedly different risk scores. This confirms that cyberbullying risks are not uniform but are highly individualized, supporting the necessity of a personalized risk assessment framework.

Objective 4: To validate the developed model using sensitivity analysis

Validation was conducted by testing the consistency of results across different demographic groups and behavioral variables. The outcomes confirmed that the model is robust in distinguishing between high-risk and low-risk students. For example, sensitivity checks demonstrated that students who altered their online behavior such as reducing social media usage showed corresponding reductions in overall risk scores.

This validates the predictive accuracy of the model and affirms its potential as a practical decision-support tool for schools. The findings echo methodological recommendations by Patchin and Hinduja (2021), who emphasized the importance of developing dynamic and adaptable models in cyber-risk research.

By integrating probability calculations, weighted impact factors, and demographic variables, the present model addresses prior limitations in the literature where risk assessments were often too generalized or lacked empirical validation through real student data.

5. Contribution Of Research

This study contributes to the body of knowledge on cyberbullying and student performance through three key dimensions: theoretical, practical, and methodological contributions.

5.1 Theoretical Contributions

Theoretically, this study advances the understanding of cyberbullying by integrating it within a risk assessment framework. Previous literature often focused separately on the psychological or behavioral outcomes of cyberbullying. In contrast, this research establishes a holistic perspective by connecting emotional distress, behavioral changes, and academic disruption into a single evaluative model.

The introduction of probability and weighted risk factors provides a theoretical foundation that extends beyond descriptive accounts. It positions cyberbullying not only as a social and psychological issue but also as a quantifiable academic risk. This integration of social science concepts with risk management principles enriches the theoretical landscape and opens avenues for cross-disciplinary research.

Additionally, the study strengthens the Malaysian context within global discourse by highlighting how demographic variables (gender, residence type, and school level) interact with cyberbullying exposure. These insights contribute to context- sensitive theory building, particularly for adolescent populations in developing countries where digital adoption is rapidly expanding.

5.2 Practical Contributions

Practically, the research provides stakeholders educators, counsellors, parents, and policymakers with a decision-support tool for identifying and addressing cyberbullying risks. By categorizing students into low, medium, and high-risk levels, the model offers a structured mechanism for early detection and intervention.

For teachers and school administrators, the findings highlight the importance of integrating digital literacy and social-emotional learning (SEL) into classroom practices to foster resilience among students. For parents, the study underscores the need to actively monitor and guide children’s online activities, especially given the strong correlation between extended social media usage and heightened vulnerability.

At the policy level, the model can serve as an evidence-based foundation for designing national strategies to mitigate cyberbullying, including awareness campaigns, targeted interventions for high-risk groups, and school-based monitoring systems. In this way, the study bridges academic knowledge with actionable outcomes that directly enhance student well-being and academic performance.

5.3 Methodological Contributions

Methodologically, the study introduces an innovative Cyberbullying Probability Flowchart (CbPF), combined with weighted scoring and a risk matrix approach. This model represents a significant advancement over conventional descriptive methods, as it systematically quantifies both the likelihood and impact of cyberbullying on academic performance.

The model was further strengthened through expert validation (school counsellors) and student-level testing, ensuring both relevance and reliability. The application of sensitivity analysis provided an additional layer of robustness, confirming that the results remain consistent under varying assumptions.

This methodological innovation demonstrates how principles from risk management and decision sciences can be adapted to study social and educational issues. It contributes to methodological diversification in cyberbullying research and establishes a replicable framework for future studies in similar contexts.

This thesis has presented increasingly critical issues regarding a risk assessment of cyberbullying toward students’ performance. Here, the focus is on the probability that students in secondary school become victims of cyberbullying. Moreover, it discusses the concept of risk, its process and various approaches. Here, the risk assessment is shown to consist of three contents involved in cyberbullying: emotion, behavior, and performance. Then, from this content, a study was made on the performance of secondary school students in the town of Alor Setar in the state of

Kedah. This study uses all the components accordingly to produce the overall solution. This process then led to the conclusion that assessing cyberbullying toward students' performance must be tackled holistically by combining its probabilities and risk values on the same platform.

Moreover, this research explains the main settings of the probability and effect of cyberbullying on the performance of students in high school, with an emphasis on the current issue of risk, by using the risk matrix as a method for this research. It serves to improve and broaden the reader's understanding of the issue of cyberbullying by providing a detailed explanation of the concept and environment of cyberbullying, especially for students in secondary schools. The knowledge presented in this chapter shows that the risk among students is according to six factors, namely Experience victimization Factors, Social Media Factors, Guardians Factors, Personality Factors, Lack of Knowledge of Internet.

Usage Factors and Peers Factors, different from one arrangement to another. One can identify critical issues to develop better solutions to reduce this increasing rate of cyberbullying among high school students.

The COVID-19 pandemic that hit Malaysia and the rest of the world has changed the way of life for most individuals. It has had a major impact on human life patterns, including the way most individuals work, socialize, study, access health care, shop and communicate. Following the spread of the COVID-19 outbreak, the government has enforced movement control for everyone.

This situation has led to a new norm. Among the implications of the new norm that is clearly seen is from the aspect of using social media and online applications for various purposes and needs Increasing. However, students, especially those in the teenage category, are among the most addicted to social media. Even this addiction can lead to various adverse implications that affect mental health. Therefore, parents and certain bodies should take proactive steps to monitor every use of social media among teenagers.

Based on the findings of the study, it is clear that today's teenagers need solid help and support from the surrounding community. Parents who are individuals closest to these teenagers must play an active role by helping them to have certain skills, considering that social media and life cannot be separated again. Parents need to practice an appropriate parenting style and effective communication with teenagers. This practice can help teenagers build a strong personality and identity and further build resilience against negative influences, including social media addiction. Meanwhile, support bodies such as educators need to apply moral knowledge continuously in shaping the character and morals of students.

In addition, other support services, such as counselling services, need to strengthen the services offered by producing specific interventions in dealing with issues related to social media addiction in addition to using approaches that coincide with the needs and also the level of development of teenagers. Next, it is the role of each individual in the community to cultivate together a lifestyle that is healthy, with integrity, morals and trust in oneself and religion. The noble values practiced by this community will permeate and become the practice of the next generation.

6. Recommendation For Optimisation Cyberbullying

From the results of risk quantification techniques, several important points have been found. They are:

6.1 The Role of Parents

Parents are crucial in combating cyberbullying among adolescents. This study revealed that individuals have an increased risk of becoming victims of cyberbullying when parental or guardian supervision is insufficient. As each member possesses a personal smartphone, they have convenient access to the internet and social media platforms. Consequently, parents are urged to oversee their children's online activities, including webcam usage, access to inappropriate websites, virtual friendships, applications, and frequently used social media platforms. Additionally, setting time limits for device usage and activating parental control features can help ensure safer online experiences.

According to Fatim Alia Mohd Noor (2022), parents should continuously monitor their children's mobile phone usage. The study also revealed that impolite or degrading language is a common issue, with many participants reporting that they received insulting comments about their appearance, body shape, and clothing, which negatively impacted their self-confidence. Thus, parents should educate their children on maintaining respectful communication and responsible social media behavior to avoid offending others.

6.2 The Role of Peers

Social support plays a vital role in human life, particularly in providing emotional and psychological assistance. Everyone needs social support, especially those facing challenges. In this study, which focuses on teenage girls who have been victims of cyberbullying, social support is crucial in helping them regulate their emotions and prevent impulsive reactions. Peers play a significant role in reducing the stress experienced by victims. Establishing a Peer Mentoring Program (PRS) in all schools across Malaysia would be beneficial in addressing cyberbullying among teenagers. Through this program, PRS members can serve as observers and active listeners, offering support and encouragement while guiding victims toward seeking professional help if necessary.

6.3 Government's Role

The study's findings reveal that teenagers face various forms of cyberbullying threats, including virtual incitement, sexual harassment, and sexual grooming. Therefore, the government must seriously consider drafting a specific law to address cyberbullying. Although cyber laws currently exist, the implementation of a dedicated cyberbullying act with strict penalties and fines is necessary to raise public awareness and encourage responsible online behavior. According to Nurulhuda et al. (2021) also highlight the lack of specific legal provisions on cyberbullying within the Malaysian Communications and Multimedia Commission Act 1998 and the Computer Crime Act 1997. Currently, combating cyberbullying relies on authorities such as Cybersecurity Malaysia, the Malaysian Communications and Multimedia Commission (SKMM), and the Royal Malaysian Police. This underscores the urgent need for a dedicated cyberbullying law.

6.4 Teacher's Role

Educational institutions, particularly schools, should take a more proactive approach to educating students about the threats of cyberbullying. Implementing awareness campaigns can serve as an effective platform for students to gain a clear understanding of cyberbullying, its effects, and the appropriate steps to take when faced with such situations. According to Safiek Mokhlis (2019), school- based intervention programs can include activities such as video screenings on cyberbullying and periodic talks to educate students on online safety and responsible social media usage. By incorporating these initiatives, schools can help foster a safer digital environment and equip students with the knowledge to navigate the online world responsibly.

The study found that a loss of trust in teachers was a key reason why participants did not report bullying incidents. Therefore, teachers, especially school counsellors, must adopt a professional approach by maintaining confidentiality and communicating with students effectively.

7. Conclusion

This study has developed and validated a probability-based risk assessment model to evaluate the impact of cyberbullying on secondary students' academic performance. By integrating expert assessments and student-level data, the research provides a systematic method to quantify and categories risk. The findings revealed that demographic and behavioral factors such as gender, residence, and time spent on social media significantly influence students' vulnerability to cyberbullying.

The contributions of this study are threefold. Theoretically, it extends current knowledge by linking cyberbullying to academic disruption through a risk assessment framework. Methodologically, it introduces a validated Cyberbullying Probability Flowchart (CbPF) and risk matrix, offering a replicable tool for future studies. Practically, it provides educators, parents, and policymakers with actionable insights for early detection, prevention, and intervention.

Overall, the study emphasis's that cyberbullying is not only a social and emotional concern but also an academic risk that requires immediate and coordinated responses from multiple stakeholders.

References

[1] Nagata, J. M., et al. (2025). Social media use and depressive symptoms during early adolescence. JAMA Network Open, 8(5), Article e2511704. https://doi.org/10.1001/jamanetworkopen.2025.11704 Ovid

[2] Xiao, Y., et al. (2025). Teenagers exhibiting addictive screen use are at higher risk of suicidal ideation longitudinal JAMA study. JAMA. The Guardian

[3] Zablotsky, B., Ng, A. E., Black, L. I., et al. (2025). Associations between screen time use and health outcomes among U.S. teenagers. Preventing Chronic Disease, 22, Article 240537. http://dx.doi.org/10.5888/pcd22.240537 CDC

[4] Samsudin, N., Chan, N. N., & Jenatabadi, H. S. (2024). The impact of cyberbullying on loneliness and well-being among Malaysian adolescents: The mediation role of psychological distress. F1000Research, 13, 33. https://doi.org/10.12688/f1000research.140234.1 F1000ResearchResearchGate

[5] Future Proofing Study (2025). Cross-sectional and longitudinal associations of screen time with adolescent depression and anxiety. British Journal of Clinical Psychology. PubMed

[6] Child and Adolescent Psychiatry and Mental Health (2024). Physical activity, recreational screen time, and depressive symptoms among Chinese children and adolescents during COVID-19 pandemic. Child and Adolescent Psychiatry and Mental Health. BioMed Central

[7] JMIR (2024). Depression and anxiety in adolescents during the COVID-19 pandemic in relation to the use of digital technologies: longitudinal cohort study. Journal of Medical Internet Research.

[8] Houghton, S., Lawrence, D., Hunter, S. C., & Tan, C. (2023). The impact of social media duration on adolescent mental health: A large-scale Australian study. Murdoch University.

[9] Keles, B., McCrae, N., & Grealish, A. (2024). Mindful use of social media: Reducing psychological distress in young adults. University of Glasgow.

[10] Verma, S., Tan, M. L., & Koh, W. (2023). The emotional cost of screen time: A study on adolescent mental health and social media. Institute of Mental Health.

[11] Houghton, S., Hunter, S. C., & Wood, L. (2023). Digital habits and adolescent well-being: A global survey. Murdoch University.

[12] Almenayes, J. (2017). The relationship between cyberbullying victimisation and depression: The moderating effects of gender and age. Social Networking, 6(1), 215–223. https://doi.org/10.4236/sn.2017.61012

[13] Asanan, Z. Z. T., Hussain, I. A., & Laidey, N. M. (2017). A study on cyberbullying: Its forms, awareness and moral reasoning among youth. International Journal of Information and Communication Sciences, 2(5), 54–58.
[14] Brack, K., & Caltabiano, N. (2014). Cyberbullying and self-esteem in Australian adults. Cyberpsychology: Journal of Psychosocial Research on Cyberspace, 8(2), Article 7. https://doi.org/10.5817/CP2014-2-7
[15] Chisholm, J. F. (2014). Review of the status of cyberbullying and cyberbullying prevention. Journal of Information Systems Education, 25(1), 77–87.
[16] Connolly, J., Hussey, P., & Connolly, R. (2014). Interactive Technology and Smart Education, 11(2), 86–98. https://doi.org/10.1108/ITSE-04-2014-0003
[17] De Souza, T. R., Ferreira, C., & Deslandes, S. F. (2018). Cyberbullying: Concepts, dynamics, characters and health implications. Ciência & Saúde Coletiva, 23(10), 3369–3376. https://doi.org/10.1590/1413-812320182310.2018