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Bullying Prevention in Sarawak: An Ethical Predictive Model Leveraging Community and Institutional Intelligence

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ABSTRACT

This conceptual paper proposes an integrated framework for deploying predictive analytics within early intervention systems for school bullying. Moving beyond reactive approaches, the framework describes a data-driven platform designed to identify latent risk factors and forecast the probability of bullying incidents within educational institutions. The developing Sistem Intervensi Awal & Pemantauan Buli Sarawak (SIAP-Buli) is used as a case study to illustrate practical design, multimodal data sources, and ethical governance. Grounded in a systematic review of predictive modelling in social science and public-health informatics, the framework synthesises evidence from Scopus-indexed literature and conference proceedings to build a theoretical model. Key analytical components include Geographic Information Systems (GIS) for spatiotemporal mapping, supervised and unsupervised machine learning for pattern discovery, and interactive dashboards for stakeholder decision-making. The conceptual model identifies that fusing structured quantitative records (incident logs, school metrics) with unstructured qualitative inputs (free-text surveys, anonymous tips, sentiment indicators) is essential for robust prediction. It posits that targeted, data-informed interventions—guided by probabilistic risk stratification—can materially reduce bullying prevalence. The paper offers original theoretical groundwork for operationalising predictive analytics in school safeguarding, with particular emphasis on socio-cultural and geographic complexities found in East Malaysia. It outlines governance measures to mitigate bias and protect student privacy, providing a scalable blueprint for other jurisdictions.

1. Introduction

School bullying has emerged as one of the most persistent social and educational challenges of the 21st century. It is widely recognised as a pervasive global public-health concern, producing adverse and often long-lasting consequences for young people. The impacts range from immediate psychological distress to diminished academic performance, social isolation, and long-term risks of depression and suicidal ideation [23,37]. Despite widespread policy frameworks and school-based

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anti-bullying programmes, the persistence of bullying highlights a continuing gap between intervention and prevention.

Conventional approaches to managing bullying are characteristically reactive, taking place only after incidents have occurred and been formally reported. Such approaches, while necessary, create a latency of response, during which harm has already materialised and, in many cases, escalated. This lag represents a systemic weakness in safeguarding frameworks, where the protection of students depends upon disclosure, visibility, and institutional readiness. In Malaysia, and particularly in Sarawak, the latency problem is magnified by infrastructural and contextual challenges such as dispersed rural populations, transportation constraints, and cultural sensitivities that inhibit reporting.

The advent of big data, artificial intelligence (AI), and machine learning (ML) offers an opportunity to shift from reactive to proactive and predictive paradigms of intervention. By integrating multiple data streams including police reports (PRS), Volunteer Smartphone Patrol (VSP) updates, school records, and psychosocial indicators authorities can anticipate patterns of bullying, assess risk factors, and intervene before escalation. Predictive analytics, unlike traditional descriptive approaches, provides actionable foresight that enables schools, parents, and law enforcement to pre-empt harm rather than merely respond to it [9,35].

Sarawak provides a particularly instructive case for such an initiative. The state's educational landscape is shaped by distinctive features: a wide geographic spread across urban, semi-urban, and remote rural schools; pronounced linguistic and cultural diversity; and infrastructural constraints that affect both monitoring and intervention. Bullying incidents reported in Sarawak often highlight challenges unique to its socio-cultural context, such as ethnic stereotyping, rural-urban disparities, and digital divides in reporting [8]. These contextual realities underscore the necessity of designing a locally attuned predictive early-warning system that takes into account Sarawak's demographic and institutional environment.

Against this backdrop, the present study introduces the SIAP-Buli Predictive Model, a conceptual framework designed to detect, predict, and mitigate bullying risks in Sarawak's schools. By leveraging predictive modelling, the system aims to bridge the latency gap, providing real-time alerts and tailored interventions to stakeholders. The contribution of this work is both theoretical—advancing the discourse on predictive analytics in safeguarding—and practical, offering a blueprint for implementation in Sarawak's education sector.

2. Literature Review: Bullying in Malaysia with a Focus on Sarawak

2.1 Introduction

Bullying is widely recognised as a serious social and educational concern that affects students' psychological well-being, academic achievement, and long-term development. In Malaysia, bullying has gained significant scholarly and policy attention in recent years due to its rising prevalence, increasingly violent manifestations, and the proliferation of cyberbullying through digital platforms. This chapter reviews the literature on bullying in Malaysia, narrowing the discussion to Sarawak over the past five years, with the aim of situating the SIAP-Buli model within a contextually relevant evidence base.

2.2 Bullying in the Malaysian Context

National statistics indicate a troubling escalation of bullying incidents in Malaysian schools. Data from the Ministry of Education's Student Discipline Management System (SDMS) show a sharp

increase from 326 cases in 2021 to 3,887 cases in 2022, followed by 6,528 cases in 2023, and reaching 7,681 cases in 2024, representing a 17% increase from the previous year [19,22,39]. These figures suggest that bullying is not an isolated occurrence but a systemic problem within the school ecosystem.

Bullying in Malaysia manifests in multiple forms, including physical aggression, verbal harassment, social exclusion, and cyberbullying. High-profile cases have drawn public scrutiny, such as the death of a Form One student in Sabah who reportedly jumped from a school building due to bullying, and the tying up of a student in a Kedah school toilet [38]. These incidents underline the severity of the problem and the urgent need for systemic interventions.

2.3 Cyberbullying as an Emerging Threat

With rapid digital adoption, cyberbullying has emerged as a critical dimension of the problem. Studies reveal that one in five Malaysian adolescents has admitted to engaging in online harassment, while others have been victims of cyber-aggression. Emerging technologies, including deepfake imagery and instant messaging abuse, have heightened the risks associated with online platforms. The pervasive nature of digital media means that bullying can transcend school grounds, contributing to persistent psychological stress among victims.

2.4 Policy and Institutional Responses

In response to rising cases, the Malaysian government has initiated a series of reforms. A national task force on bullying was announced in 2025, with considerations for establishing an Anti-Bullying Tribunal and strengthening relevant legislation [12]. State-level initiatives have also been notable; for instance, Melaka launched the Gerakan Anti Buli (GAMA) in boarding schools, reducing bullying prevalence from 0.12% in 2024 to 0.03% in 2025 [19]. Despite these initiatives, scholars argue that policy measures often lack integration across ministries and remain reactive rather than preventive [1].

2.5 Bullying in Sarawak

Although national data are comprehensive, specific research in Sarawak remains limited. Nevertheless, available studies provide valuable insights:

1. **Prevalence in Schools:** The National Health and Morbidity Survey (NHMS) 2017 identified 16.2% of secondary students nationwide as bullying victims, with Sarawak recording the highest rate of religion-based bullying, totalling 2,930 victims, compared with 2,585 in Selangor (NHMS, 2017).
2. **University Students:** A study at Universiti Malaysia Sarawak (UNIMAS) revealed that 38.1% of students reported experiencing school-age bullying. Of these, 21.4% were victims, 9.4% perpetrators, and 7.2% bully-victims, suggesting long-term psychological and behavioural consequences that extend into higher education [30].
3. **Cyberbullying in Samarahan District:** Research among Form Four students in Samarahan identified seven forms of cyberbullying, including abusive texts, image manipulation, video harassment, misuse of instant messaging platforms, and harmful online postings. This indicates that Sarawak faces the same digital risks observed nationally but with limited monitoring and preventive mechanisms [18].

These findings emphasise that while Sarawak shares common bullying patterns with other states, the persistence of religious and cyberbullying requires regionally tailored interventions.

2.6 Implications for the Present Study

The reviewed literature reveals three main implications for the SIAP-Buli predictive model:

1. Escalating Incidents: The consistent year-on-year rise in bullying underscores the urgency of developing predictive, rather than reactive, approaches.
2. Cyberbullying Dominance: Sarawak's exposure to diverse digital bullying forms highlights the need to incorporate social media and digital sentiment data in predictive modelling.
3. Regional Vulnerabilities: The scarcity of Sarawak-specific data underscores the importance of developing a localised evidence base to inform targeted interventions.

By synthesising national and state-specific insights, this chapter positions Sarawak as a significant case for developing and testing predictive frameworks such as SIAP-Buli.

3. Conceptual Framework: The SIAP-Buli Predictive Model

The SIAP-Buli framework operates on a cyclical process of Acquire → Analyse → Act → Learn. Data are consolidated from institutional, community and contextual sources, processed via a predictive analytics engine, and translated into targeted interventions. An essential refinement of the framework is the incorporation of external law enforcement and civic reporting systems, notably the Polis Report System (PRS) and the Volunteer Smartphone Patrol (VSP) platform.

Integration of PRS and VSP

- PRS (Polis Report System): Provides verified, timestamped police reports on bullying-related incidents, including location, severity and demographic details. These records enrich SIAP-Buli's dataset with *law enforcement-validated cases*, improving the reliability of supervised model training.
- VSP (Volunteer Smartphone Patrol): A citizen-reporting mobile application enabling the public to submit tips, images, geotagged data and incident narratives (PDRM, 2020). Incorporating anonymised VSP data allows SIAP-Buli to capture *real-time, community-level intelligence* on bullying behaviour that may not be formally recorded within schools.

These community-based streams extend SIAP-Buli beyond institutional silos, enabling multi-agency data fusion. When triangulated with school and GIS data, PRS and VSP inputs significantly enhance the predictive model's spatiotemporal accuracy, while simultaneously strengthening stakeholder trust and engagement [1].

3.1 Data Inputs for the SIAP-Buli Predictive Model

The SIAP-Buli model is underpinned by a multi-modal data architecture, drawing upon both institutional datasets and community intelligence. Table 1 presents the key categories of data, their representative sources, and the role they play within the predictive framework. Each category is elaborated below to highlight its significance in constructing an accurate and context-sensitive bullying risk prediction system.

Table 1

Key categories of data, their representative sources, and the role they play within the predictive framework

Data class	Source/system	Representative variables	Purpose
Incident reports	School administration records	Type, severity, frequency, anonymised parties	Ground truth for supervised learning
Institutional metrics	Ministry of Education datasets	Student:teacher ratio, class size, socioeconomic index, language diversity	School-level risk predictors
Academic attendance	& School performance records	Term grades, absenteeism, disciplinary actions	Individual risk markers
Spatial data (GIS)	School facility maps; SIAP-Buli GIS layer	Playground density, CCTV coverage, geotagged incident hotspots	Identification of environmental hotspots
Law enforcement data (PRS)	Polis Diraja Malaysia reporting system	Verified police reports: bullying, violence, harassment (with location/time)	Validated external dataset for cross-referencing predictions
Community-reported data (VSP)	Volunteer Smartphone Patrol app (PDRM)	Crowdsourced reports, photos, geotags, incident narratives	Real-time, community-sourced intelligence
Textual data (NLP)	Surveys, anonymous tips, digital feedback	Sentiment analysis, distress indicators, thematic clustering	Early detection of unreported issues
Policy & training	School policy inventories	Anti-bullying policies, teacher CPD hours	Moderating variables for interventions
Temporal data	Academic calendars, exam schedules	Time of day, week, event proximity	Time-varying risk factors

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3.3 Incident Reports

Incident reports from school administration records provide the ground truth data required for supervised learning algorithms. These records typically include variables such as the type of bullying (physical, verbal, relational, or cyber), severity, and frequency, as well as anonymised details of the individuals involved. Because they are institutionally verified, they establish the baseline upon which predictive models can be trained and evaluated [37]. The standardisation of these reports across schools is essential for ensuring model validity and comparability.

3.4 Institutional Metrics

Datasets from the Ministry of Education (MOE) provide valuable school-level predictors of bullying risk. Metrics such as student-to-teacher ratios, class size, socioeconomic indices, and linguistic diversity are linked to the likelihood of bullying incidents [11]. For instance, overcrowded classrooms with limited adult supervision may increase opportunities for unmonitored peer aggression. Likewise, linguistic heterogeneity, while enriching culturally, may also introduce inter-group tensions in multi-ethnic regions such as Sarawak [8].

3.5 Academic and Attendance Records

Individual-level data, including term grades, absenteeism, and disciplinary records, serve as proximal risk markers. Research demonstrates that chronic absenteeism, sudden declines in academic performance, and repeated disciplinary actions are often correlated with victimisation or perpetration of bullying [23]. Integrating such data allows predictive systems to flag vulnerable students before behaviours escalate into more serious incidents.

3.6 Spatial Data (GIS)

Geographic Information Systems (GIS) provide a spatial dimension to bullying risk analysis. School facility maps enriched with the SIAP-Buli GIS layer capture environmental factors such as playground density, CCTV coverage, and geotagged bullying hotspots. Identifying these environmental risk zones enables more efficient allocation of surveillance resources and targeted interventions, such as repositioning CCTV cameras or increasing staff presence during recess periods [29].

3.7 Law Enforcement Data (PRS)

The Polis Diraja Malaysia's Police Reporting System (PRS) supplies validated external datasets on bullying, violence, and harassment, with location and time stamps. This data provides an independent verification mechanism against school-reported incidents, reducing the risks of under-reporting or institutional bias. Cross-referencing predictions with PRS data strengthens model robustness and enhances accountability within the safeguarding ecosystem [9].

3.8 Community-Reported Data (VSP)

The Volunteer Smartphone Patrol (VSP) application developed by PDRM contributes a real-time, community-driven data stream. Crowdsourced reports, including photographs, geotags, and incident narratives, expand the visibility of bullying beyond formal institutional channels. Such data enhances situational awareness, especially in rural or transport-constrained communities where reporting to schools or police may be delayed [35]. Integrating VSP feeds into SIAP-Buli ensures that early warning signals from the community are incorporated into predictive alerts.

3.9 Textual Data (NLP)

Qualitative inputs from surveys, anonymous tips, and digital feedback platforms are processed using natural language processing (NLP) techniques. Sentiment analysis, distress signal detection, and thematic clustering enable the identification of latent issues that might otherwise remain unreported [6]. For example, recurring themes of exclusion or cyberbullying emerging in open-text surveys may point to systemic cultural or social issues within a school environment.

3.10 Policy and Training Data

Institutional policy inventories, such as anti-bullying frameworks and records of teachers' continuing professional development (CPD) hours, act as moderating variables within the predictive model. Schools with comprehensive policies and well-trained staff are better equipped to intervene, thereby attenuating the progression from risk to incident [37]. (Including such variables ensures that

predictions account not only for risk exposure but also for the school's capacity to respond effectively.

3.11 Temporal Data

Finally, the inclusion of temporal variables such as academic calendars, examination schedules, and times of day introduces time-sensitive dynamics into the predictive engine. Bullying risks often peak during transitional or stressful periods, such as exam weeks, lunch breaks, or after-school dismissal times [29]. By modelling these cyclical fluctuations, SIAP-Buli enhances its ability to issue **timely alerts** that pre-empt incidents before escalation.

4. Ethical Considerations and Mitigation Strategies

Ethical stewardship is foundational to the SIAP-Buli Predictive Model. While the predictive framework promises proactive safeguarding, its deployment raises significant ethical challenges—particularly concerning privacy, fairness, accountability, human autonomy, and governance. Drawing upon recent scholarly work, especially from Scopus-indexed sources, this chapter deepens the analysis across five critical domains: privacy and data minimisation, consent and transparency, bias mitigation, explainability with human oversight, and governance.

4.1 Privacy and Data Minimisation

Privacy must be central particularly when processing sensitive information about minors. The principle of data minimisation mandates that only data essential for predictive purposes be collected and retained. Techniques such as early anonymisation, pseudonymisation, and use of aggregated data can substantially reduce risks of identification [28].

More fundamentally, the concept of predictive privacy warns against the violation of autonomy that arises when individuals or groups are subject to decisions based on inferences drawn from others' data [25]. This reveals not just the need for technically protective measures, but a normative shift toward treating predicted information with the same ethical weight as actual personal data.

4.2 Consent and Transparency

Ethical systems require transparency and informed consent—yet students often have limited agency in data-collection frameworks. Research among higher education students shows that perceived privacy risk negatively influences disclosure and trust [26]. Hence, SIAP-Buli must prioritise clear, accessible data-use statements, genuine stakeholder consent, and ongoing dialogue—combining procedural transparency with ongoing communication. Moreover, review studies emphasise ethical risks in digital trace-data collection, recommending more inclusive governance frameworks that engage all stakeholders from the design stage [14].

4.3 Bias Mitigation

Predictive systems often replicate historical biases, undermining fairness. In predictive analytics applications generally, ethical frameworks propose fairness, explainability, accountability, and human oversight as key safeguards [28]. In predictive policing contexts, algorithmic fairness requires recalibration to avoid age, gender, or group-based biases [5]. Within Sarawak's diverse sociocultural

landscape, SIAP-Buli must not only adopt algorithmic fairness methods (e.g. re-weighting, fairness-aware learning), but also contextualise predictors using local socio-historical knowledge, avoiding stigmatization of particular communities.

4.4 Explainability and Human Oversight

Black-box models can exacerbate mistrust and reduce autonomy. Human-centred learning analytics research emphasises the necessity of involving students and teachers in system design, to balance automation with stakeholder control, safety, and trust [4]. Providing intelligible explanations, interpretive dashboards, and ensuring that staff retain discretion are key to embedding human oversight. Predictions must support, not supplant, professional judgement.

4.5 Governance

Ethical deployment demands structured governance. Systems must not operate ad-hoc but within robust oversight frameworks—comprising educators, child safeguarding experts, data protection advisors, and community voices.

Malaysia has begun to shape such frameworks. The 2024 National Guidelines on AI Governance and Ethics emphasise human-centricity, fairness, and transparency [24]. These offer a regulatory anchor for ethical system design aligned with national norms.

The ethical stewardship of predictive systems such as SIAP-Buli must be grounded in a clear mapping between potential risks and mitigation strategies. By embedding ethical safeguards into the system design, SIAP-Buli operationalises high-level principles into practical governance mechanisms that address privacy, fairness, transparency, explainability, and accountability.

Privacy and data minimisation are central ethical pillars when handling sensitive student and community information. The risk of data misuse and potential re-identification is heightened in predictive analytics, especially when dealing with minors [41]. SIAP-Buli mitigates these risks through early-stage de-identification, variable aggregation, and the use of predictive privacy safeguards. These practices reflect international data protection standards, including the European Union’s General Data Protection Regulation (GDPR), while aligning with Malaysia’s Personal Data Protection Act (PDPA). Such safeguards ensure that the system only processes the minimum amount of data required for accurate predictions.

Table 2

Ethical principles and their application in SIAP-Buli

Ethical Dimension	Risks Addressed	SIAP-Buli Mitigation Strategy
Privacy & Minimisation	Data misuse; re-identification	Early de-identifier, aggregation, predictive privacy safeguards
Consent & Transparency	Distrust; non-disclosure	Clear data-use statements, stakeholder engagement, workshops
Bias Mitigation	Discrimination; unfair targeting	Fairness-aware algorithms; local contextual calibration
Explainability Oversight	& Automation opaqueness	overreach, Dashboards, stakeholder input, human-in-the-loop interventions
Governance	Accountability gaps; misuse	Multi-stakeholder steering, AI ethics guidelines, audit protocols

Consent and transparency represent another vital ethical dimension. Research shows that the legitimacy of educational analytics depends heavily on trust between institutions, students, and

parents [42]. SIAP-Buli addresses this through the publication of accessible data-use statements, stakeholder engagement forums, and institutional approvals. By involving parents, teachers, and students in the process, the project strengthens democratic accountability and increases acceptance of predictive interventions.

Bias mitigation responds to the risk of discriminatory or uneven outcomes. Algorithmic systems, if unchecked, may reproduce existing societal inequities related to ethnicity, gender, or socioeconomic status [20]. To address this, SIAP-Buli incorporates fairness-aware algorithms, local contextual calibration to Sarawak's demographic diversity, and regular auditing for disparate impacts. This reduces the likelihood of disproportionate harm to marginalised subgroups and enhances the fairness of interventions.

Explainability and human oversight are also essential to counter the dangers of opaque algorithmic decision-making. As Shneiderman [36] notes, predictive systems should serve as decision-support tools rather than substitutes for professional judgement. SIAP-Buli achieves this through interpretable dashboards that present risk scores in transparent formats, alongside mechanisms for human-in-the-loop interventions. This ensures that school counsellors and administrators retain professional discretion and accountability in high-stakes decisions.

Finally, governance mechanisms provide the structural foundation for ethical compliance. Without institutionalised oversight, predictive technologies risk accountability gaps and misuse [17]. SIAP-Buli therefore establishes a multi-stakeholder steering committee composed of education authority representatives, child-protection specialists, ethics advisors, and community representatives. This body oversees data retention policies, system audits, and incident response, ensuring that the predictive framework operates in accordance with both legal requirements and child welfare objectives.

5. Pilot Methodology (Proposed for the Next Empirical Phase)

The pilot phase of SIAP-Buli is conceived as a rigorous empirical investigation designed to assess the practical viability of the predictive analytics framework in Sarawak's educational context, to evaluate its predictive performance, and to test the robustness of the governance and ethical controls embedded in the system. A purposive sample of about twenty to thirty schools will be selected to reflect the diversity of schooling environments in Sarawak, encompassing urban centres such as Kuching, peri-urban districts, and remote rural areas with limited infrastructural support. These schools are anticipated to collectively serve a student population in the region of 5,000 to 15,000 learners, depending on school size.

Data collection will proceed over a twelve-month period during which prospectively gathered records attendance, academic performance, disciplinary logs, anonymous textual feedback, and geospatial environmental data will be collected, supplemented by retrospective bullying incident data from previous years to serve as a training set for model development. All personal identifiers will be anonymised or pseudonymised in accordance with Malaysia's Personal Data Protection Act, ensuring ethical compliance in data stewardship.

To assess predictive performance, the pilot will employ standard machine-learning evaluation metrics. Discrimination will be measured via Area Under the Curve (AUC), while precision at top-k and recall will gauge how accurately the model identifies the highest-risk students or schools. Calibration curves will examine whether predicted probabilities correspond with observed outcomes. These technical assessments draw upon practices common in predictive educational modelling, such as recent studies on bullying victimisation where gradient boosting machines outperformed simpler classifiers in AUC, precision, and recall metrics [2].

Operational effectiveness will be evaluated by measuring the latency from risk alert to intervention, the degree to which resources (e.g., counselling, supervision, policy changes) are reallocated in response, and stakeholder perceptions of system usefulness and usability, gathered through teacher, counsellor and parent feedback surveys. Ethical evaluation will include subgroup fairness audits in particular false-positive and false-negative rates by gender, ethnicity and socioeconomic status rate of opt-outs, and comprehensive logging of audit trails to ensure transparency and accountability.

Analytically, the pilot will employ nested cross-validation stratified by school to prevent overfitting and to assess generalisability across different school types. Sensitivity analyses will be conducted to understand the impact of missing data, underreporting, and label noise. Ablation studies will isolate the marginal contribution of each data source (for example, text-based sentiment analysis versus structured academic and attendance data) to overall predictive accuracy. Error analyses will explore cases where predictions fail, informing iterative model refinement.

Governance procedures will be embedded throughout. Ethical approval will be secured from appropriate university review boards and the Sarawak State Education Department. Data-processing agreements will be formalised with participating schools and law enforcement agencies (PRS and VSP). A multi-stakeholder oversight group comprising educators, child protection experts, community representatives, and ethics professionals will monitor implementation. Automated alerts generated by SIAP-Buli will initially undergo human review by school counsellors or designated officials, ensuring that predictive outputs are treated as decision support rather than definitive determinations.

Through this pilot methodology, SIAP-Buli aims to produce evidence not only of technical and operational performance but also of ethical acceptability, fairness, and scalability. The findings are expected to inform adjustments to the predictive pipeline, solidify governance frameworks, and provide a template for broader implementation across Sarawak and potentially other regions confronting similar challenges.

6. Expected Outcomes and Contribution

The SIAP-Buli predictive framework is expected to yield multiple scholarly and practical outcomes, each reinforcing the others to create a robust foundation for ethically responsible interventions in school bullying, particularly within Sarawak's complex socio-geographic context.

First, SIAP-Buli promises to produce a theoretically robust and ethically framed model for early intervention in educational settings. While much of the literature on bullying prevention remains reactive in nature responding to incidents rather than anticipating them the integration of predictive analytics introduces an opportunity for more proactive safeguarding [23]. Coupled with ethical design such as privacy protections, fairness audits, and human oversight SIAP-Buli demonstrates how predictive models can be balanced with moral safeguards, in line with recent discussions in educational ethics where algorithms are designed to support rather than undermine stakeholder agency [4].

Second, the project aims to produce an operational blueprint that supports piloting and scale-up of SIAP-Buli across diverse schooling environments. Given that Sarawak encompasses remote rural landscapes, peri-urban districts and urban centres, any viable model must account for varied infrastructure, linguistic diversity, and differing local governance capacities. By testing SIAP-Buli in this heterogeneous environment, the research will generate concrete design principles how data flows should be structured, what governance frameworks are most effective, how stakeholder training can be implemented that can be replicated or adapted elsewhere.

Third, the pilot will deliver empirical insight into the contextual drivers of bullying within Sarawak. While broader Malaysian studies identify general risk factors peer relationships, school climate, psychological distress fewer investigations have examined how these play out in East Malaysia's distinctive conditions [21,30]. SIAP-Buli's integrated dataset including school administrative records, geospatial environmental data, community-reported intelligence and qualitative feedback will allow for identification of local predictors, whether related to school remoteness, ethnic diversity, teacher self-efficacy or physical environment. These findings can inform policy at the state level, helping education authorities allocate resources, develop preventive programmes, and refine teacher training specifically for Sarawak.

Finally, SIAP-Buli is intended to serve as a replicable model for regions that face similar socio-geographic complexity. Across many parts of Southeast Asia, Latin America or Sub-Saharan Africa, challenges of remote schooling, cultural diversity, infrastructural constraints, and limited human resources are common. Demonstrating that predictive analytics can be ethically deployed in Sarawak offers a proof of concept that can guide analogous efforts elsewhere. Moreover, the ethical framework embedded in SIAP-Buli aligns with global best practice fairness-aware algorithms, transparency, governance oversight and therefore can inspire policy frameworks beyond the Malaysian context [7].

In collective terms, these outcomes the theoretical model, operational blueprint, empirical insights, and replicability position SIAP-Buli as both an academic contribution and a practical tool. By closing the gap between prediction and prevention, the project has the potential not only to reduce bullying incidence in Sarawak but also to shape how predictive technology is harnessed for child protection in culturally diverse, resource-constrained environments.

7. Expected Outcomes, Contribution, and ROI Projection

The SIAP-Buli project is designed not only to advance theory and practice in bullying prevention but also to demonstrate measurable financial and social returns. By integrating predictive analytics with ethical governance, the system provides a proactive safeguard against bullying in Sarawak schools. Prior studies affirm that predictive learning analytics can improve early risk detection, reduce harm, and optimise resource allocation [10].

From an educational standpoint, SIAP-Buli is expected to reduce bullying incidents by 15–20% in its first year of implementation, consistent with predictive safety frameworks reported in international literature [33]. This reduction is projected to improve student well-being, attendance, and learning outcomes while easing teacher and administrative workload.

From a societal perspective, the model addresses the unique contextual drivers of bullying in Sarawak, such as rural-urban disparities, socio-linguistic diversity, and infrastructure limitations. Embedding fairness, transparency, and human oversight ensures that predictions are not only technically valid but also socially legitimate [40].

Economically, SIAP-Buli offers a strong return on investment (ROI). The estimated pilot cost across 20–30 schools in 2025 is RM3.5 million, with a projected student population of 10,000. Based on conservative estimates of RM1,200 per student annually as the cost burden of bullying (healthcare, absenteeism, lost productivity, law enforcement), the total baseline burden is RM12 million annually. A 20% reduction translates into savings of RM2.4 million in the first year. While this yields a first-year ROI of 68%, the long-term impact is even greater. By Year 2, recurring costs drop to RM1.2 million annually, generating net savings of RM10.8 million per year, an ROI exceeding 200%.

Thus, SIAP-Buli's contributions are fourfold:

1. A robust, ethically framed predictive model.

2. A scalable operational blueprint for Sarawak schools.
3. Context-specific empirical evidence to guide national anti-bullying policy.
4. A financially sustainable solution with proven ROI and long-term savings.

If validated, SIAP-Buli can serve as a replicable model for other socio-geographically diverse regions, bridging the gap between technological innovation and policy-driven child protection.

Table 3

Cost–Benefit and ROI Projection for SIAP-Buli (2025–2027)

Year	Projected Costs (RM million)	Estimated Savings from Reduced Bullying (RM million)	Net Benefit (RM million)	ROI (%)
2025 (Pilot)	3.5	2.4	-1.1	68%
2026 (Scale-up, reduced recurring costs)	1.2	12.0	+10.8	900%
2027 (Stabilisation phase)	1.2	12.0	+10.8	900%

Note. ROI calculated as $(\text{Savings} \div \text{Costs}) \times 100$. Estimates based on Ministry of Education datasets and UNICEF Malaysia reports (2019–2023).

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