Journal of Information Technology Education: Innovations in Practice

An Official Publication of the Informing Science Institute InformingScience.org

JITEiip.org

Volume 25, 2026

A Multidimensional Evaluation of a School Disengagement Predictive Model Across Technical, Usability, and Acceptance Dimensions

Laura Lim Sie-Yi*	Universiti Utara Malaysia, Kedah, Malaysia	lauralim041@gmail.com
Noraziah ChePa	Universiti Utara Malaysia, Kedah, Malaysia	aziah@uum.edu.my

* Corresponding author

Abstract

Aim/Purpose	The aim of this study is to conduct a comprehensive evaluation of the proposed predictive model by validating its technical performance, usability, and acceptance.
Background	School disengagement is a persistent challenge that can lead to adverse academic and social outcomes if not identified early. Although predictive and data-driven approaches have been proposed to support early intervention, many existing systems lack comprehensive evaluation across technical performance, usability, and user acceptance, limiting their adoption in real school environments. This gap motivated the development and evaluation of a school disengagement predictive model implemented through the *MyBuddy* mobile and web-based systems.
Methodology	A six-phase methodology was adopted in this study to systematically develop, implement, and evaluate the proposed school disengagement predictive model through the implementation of *MyBuddy*. The methodology comprised six sequential phases: factor identification, model design and development, model verification, model refinement, model validation, and performance evaluation. Initially, the predictive model was developed based on 13 contributing factors identified through systematic literature reviews. Following expert verification, the model was refined to incorporate an additional factor, resulting in a final model consisting of 14 contributing factors.

Accepting Editor Torsten Reiners │ Received: December 25, 2025 │ Revised: April 20, June 30, August 1, 2026 │ Accepted: August 7, 2026.

Cite as: Sie-Yi, L. L., & ChePa, N . (2026). A multidimensional evaluation of a school disengagement predictive model across technical, usability, and acceptance dimensions. *Journal of Information Technology Education: Innovations in Practice, 25,* Article 37. https://doi.org/10.28945/5863

The verified model was subsequently implemented through the development of *MyBuddy*, which was deployed as both web- and mobile-based applications. A comprehensive evaluation was then conducted to assess both the technical quality of the system and the effectiveness of the predictive model. Technical evaluation involved 27 information technology experts who assessed the system's functionality, reliability, and overall performance. Subsequently, 27 intended users evaluated the system for usability, interface design, perceived usefulness, and user satisfaction. Finally, predictive performance was evaluated using data from 50 secondary school students across two schools by comparing *MyBuddy*'s predictions with counsellors' assessments using confusion matrix analysis. This comprehensive methodology enabled a rigorous evaluation of the predictive model's conceptual validity, technical robustness, usability, and predictive performance in supporting the early identification of students at risk of school disengagement.

Contribution: The findings contribute to sustainable educational innovation and align with Sustainable Development Goal 4 (Quality Education) by supporting inclusive and timely intervention strategies.

Findings: The findings indicate that the proposed model can effectively support the early identification of students at risk of school disengagement by classifying students into low-, medium-, and high-risk categories. The prediction results showed reasonable agreement with school counsellors' professional assessments, supporting the role of *MyBuddy* as a decision-support tool rather than a standalone diagnostic system. In addition, the usability and user acceptance evaluations demonstrated positive responses from school counsellors, particularly regarding ease of use, interface clarity, and suitability for routine use in school counselling via a mobile-based platform.

Recommendations for Practitioners: These findings indicate that the system is accurate, practical, user-friendly, and well-suited for integration into real-world school counselling workflows.

Recommendations for Researchers: Future work will focus on improving model accuracy through larger, more diverse datasets, algorithm enhancements, and broader validation across varied educational contexts.

Impact on Society: The study demonstrates the feasibility of integrating predictive analytics with user-centred design to support early identification of school disengagement, for use in schools and by the Ministry of Education.

Future Research: Future work should focus on improving the model through larger and more diverse datasets, including longitudinal data, and by integrating advanced analytical techniques to enhance predictive performance. Broader stakeholder involvement and system integration with existing school platforms are also recommended to support scalability, adoption, and long-term impact.

Keywords: model validation, predictive model, school disengagement, technical testing, usability, acceptance testing

INTRODUCTION

School engagement is a multidimensional meta-construct that encompasses, among other things, the behavioural, emotional, and cognitive components of attitudes towards the school and its community, as well as the interpretation of these attitudes in their complexity (Martins et al., 2021). To put it another way, school disengagement is detrimental to involvement in the educational process, including people, activities, goals, beliefs, and the overall school environment, hindering productive educational outcomes and connections to school and community, and eventually resulting in students dropping out of school (Szabó et al., 2024). Empirical evidence consistently identifies disengagement as a strong precursor to dropout, making it a critical area for early intervention.

The prevalence of school dropout among teens remains a significant global issue, depriving them of educational opportunities and limiting their future prospects. Previous research indicates that the dropout rate for middle and upper secondary school students globally ranges from 17% to 50%, with developing countries exhibiting a higher prevalence (Skenderidou et al., 2025). Because it has a considerable influence on the next generation of Malaysians, the problem of student dropout is a source of great concern (Mikkay et al., 2023; Roslan et al., 2024). These individuals are more likely to have future financial difficulties, social criticism, fewer work opportunities, and lower financial compensation. The consequences extend beyond the individual, affecting families, communities, and society at large, including disrupting the adolescent's life, entering the illegal labour market at a young age, perpetuating a cycle of poverty, and engaging in delinquent activity (Vázquez-Nava et al., 2019).

Despite extensive research on dropout prevention, existing approaches are predominantly reactive and heavily reliant on academic performance indicators, often identifying at-risk students only after disengagement has become pronounced. Numerous educational innovations focus on enhancing the academic curriculum, such as gamified education (Kulkarni et al., 2025), virtual reality learning (Monk et al., 2025), and others, which aim to improve both content and teaching. These studies tend to overlook the early detection of disengagement as a multidimensional and evolving process. Thus, there is a growing need to shift the emphasis from academic factors alone to student participation in the school environment. This study introduces an innovative early predictive model of student disengagement that incorporates diverse factors rather than relying solely on academic performance. This novel innovation facilitates the early identification of at-risk pupils, enabling timely, targeted interventions to combat disengagement before it becomes deeply rooted.

This reveals a clear research gap: there is a lack of practically deployable, multidimensional predictive systems that can identify early signs of school disengagement and are systematically evaluated for usability and acceptance among school practitioners. In particular, few studies bridge the gap between predictive model development and its operational use in counselling or intervention contexts. Rather than proposing a fundamentally new algorithmic method, the originality of this study lies in integrating diverse disengagement indicators into a unified predictive framework and evaluating it in an applied school context. To address this gap, the present study introduces and evaluates a predictive model of school disengagement.

This article aims to comprehensively evaluate a school disengagement predictive model implemented through the *MyBuddy* system by examining its performance across technical, usability, and acceptance dimensions. By integrating quantitative performance analysis with user-centred evaluation, this study seeks to assess the model's reliability, practicality, and readiness for real-world deployment in school counselling contexts. This article places equal emphasis on predictive performance and user-centred considerations, recognising that practical adoption depends not only on accuracy but also on usability and acceptance. The findings are intended to provide empirical evidence to support the use of predictive technologies as decision-support tools for early identification and intervention in school disengagement.

RELATED WORKS

This section reviews prior studies on predicting school disengagement, with a focus on early identification. Past research has shown that school disengagement is influenced by multiple academic, behavioural, and contextual factors, leading to the development of various predictive models. Recent studies have increasingly used data-driven and computational approaches to identify students at risk early. By reviewing existing prediction methods and findings, this section provides the background needed to position the proposed study within current research.

SCHOOL DISENGAGEMENT PREDICTION

The potential disengagement of students may be attributed to stressors and a lack of motivation (Sumardi et al., 2023). The fact that noticeable trends have emerged in the collected data enables the development of screening tools and other proactive measures to promptly identify students at risk of dropping out and initiate timely interventions. According to Johnson and Semmelroth (2010), it is imperative to conduct screenings across all school districts, regardless of divergent graduation criteria, to identify students with educational needs requiring intervention and those at risk of falling short of standardised test benchmarks.

Henry et al. (2011) suggested that implementing an early warning index is an effective approach to assessing school disengagement, a phenomenon associated with school dropout, delinquency, and substance abuse. Nevertheless, the inquiry persists: at what juncture should an early warning system be implemented? The response indicates that optimal strategies for mitigating dropout rates should primarily focus on the primary and secondary school levels. There remains a certain level of discordance among middle and high school educators regarding the optimal starting point for intervention and dropout prevention initiatives. According to past studies, it has been demonstrated that the prognostic ability to predict dropout rates can be statistically significant as early as the sixth grade, which is about 12 years old, equivalent to secondary school level in Malaysia, with indicators of potential dropout becoming apparent even earlier in the academic trajectory (McFarland, 2023; Neild, 2009; Trinidad, 2023). Aziz et al. (2023) also studied the impact of work engagement on study performance, with subjects aged 9 to 18 years. The study found that working at this age was the primary reason for leaving school early.

The pivotal juncture in the dropout phenomenon occurs in middle school, which corresponds to the lower secondary level in Malaysia, rather than in high school. Consequently, it is imperative to allocate substantial effort and resources during the middle grades to effectively maintain adolescents' trajectory. Kiefer et al. (2014) acknowledge that middle school educators play a pivotal role in facilitating the transition to high school. Nevertheless, their primary focus is on providing specific suggestions for middle school educators to enhance their involvement in the transition process when students move on to high school. School disengagement prevention initiatives in middle schools place significant focus on the pre-high-school years. There is, however, a lack of consensus on the best way to meet the unique needs of at-risk students.

Besides, advances in educational data mining have enabled the development of predictive models using machine learning techniques such as neural networks, decision trees, and ensemble methods. Studies such as Korkmaz and Aydın (2025) demonstrate the effectiveness of these approaches in detecting early school dropout in vocational and technical education settings. Similarly, prior work has shown that such models can achieve relatively high predictive accuracy when applied to large institutional datasets. From a technical perspective, these models are valuable for handling complex, high-dimensional data and identifying hidden patterns. However, several limitations persist. First, their reliance on large, context-specific datasets limits generalisability, particularly in contexts such as Malaysia, where data access is limited. Second, many models function as "black boxes," offering limited interpretability, which reduces their usability for educators. Third, predictive performance is often prioritised over fairness, raising concerns about biased outcomes.

Recent interdisciplinary research also highlights similar challenges in predictive modelling within adolescent mental health, where models trained on self-reported data risk bias and misclassification (Xu et al., 2024). This underscores the broader issue that predictive systems in education must be evaluated not only for accuracy but also for reliability and fairness.

Existing Studies on Prediction of Early School Disengagement

Student disengagement is a complex phenomenon, with diverse interpretations, even within further and higher education, despite technological advancement. For example, students may now customise their learning through digital technologies, but student involvement in online (or conventional) learning is certain. This is probably due to several factors. First, models of engagement developed thus far have only moderately resembled models of the same construct developed in other learning environments; these models have had to be tailored to particular learning contexts, such as academic performance (Alturki & Alturki, 2021). Second, using one of a limited number of well-known algorithms on a data set in a conventional manner is a common step in the creation of knowledge models (Mishra & Silakari, 2012).

Establishing mappings between things and cognitive skills often requires some knowledge engineering and rational modelling; nonetheless, the procedure is well understood and has been applied across a wide range of learning settings. Third, it is harder to assess models of engagement than knowledge models (knowledge models are often validated by how well they predict students' future conduct) (Cocea & Weibelzahl, 2006). It can be difficult to predict disengagement on a trial-by-trial basis, especially in complicated cognitive areas (Nam et al., 2017).

Within the context of the engagement taxonomy, Delen (2011) explored several data mining techniques, including artificial neural networks, logistic regression, and decision trees, to predict student disengagement using 8 years of secondary school institutional data. The proposed models achieved an overall prediction accuracy of 81% on the holdout sample. Among the evaluated techniques, the Artificial Neural Network (ANN) architecture demonstrated the best predictive performance.

Also, within higher education datasets, Aulck et al. (2019) analysed 66,060 records of freshmen entrants using regularized logistic regression (LR), K-Nearest neighbours (KNN), neural networks (NN), random forests (RF), support vector machines (SVM), and gradient boosted trees (XGB) with an average accuracy up to 82% for each method. Similar approaches have been used to predict high school students' performances (Elbadrawy et al., 2016), low academic performances (Helal et al., 2018; Miguéis et al., 2018), student attrition risk (Mason et al., 2017), and dropout among college students (Cannistrà et al., 2022; Nagy & Molontay, 2018; Sani et al., 2020; Segura et al., 2022) and student at risk (Hung et al., 2019).

While these studies are fascinating and useful for understanding school disengagement, the settings and contexts in which they were conducted are not comparable to the Malaysian case due to limited access to student data, a different education system, and a different cultural context. A recent study conducted in Malaysia by Sani et al. (2020) focused on predicting dropout rates among B40 students enrolled in bachelor's degree programmes at public universities. The study employed Decision Tree, RF, and Artificial Neural Network (ANN) algorithms to classify attrition patterns. However, these models were designed to predict financial hardship and were fitted to the B40 group, which is not broad enough to cover all student levels. Additionally, data cleaning using the dimension-reduction process has removed more than 20,000 data points from their dataset.

These studies, focusing on data mining and analysis, depend on large datasets and can restrict the input data to match the training data. Rather than focusing on data-mining studies, the next section reviews past engagement-related studies using different methodologies.

A study by Subramainan et al. (2016) examined student engagement in the classroom, specifically using an emotion-based model with agent-based simulations. It has been found that students' emotional well-being has a significant impact on their academic engagement and overall success in the classroom. The proposed model of student engagement focuses on students' emotional responses to engagement and academic performance, which further lead to improved emotions that enhance student engagement. However, this study only examines classroom engagement as a means of enhancing academic performance and does not address external factors that can significantly influence student engagement.

Regarding engagement, Soland et al. (2019) argue that there should be more sophisticated ways to measure disengagement in the classroom that differentiate between test disengagement and general academic disengagement, and they specifically criticise current methodologies for evaluating disengagement in standardised testing environments. To properly evaluate student performance and develop interventions to address disengagement, the authors argue that it is essential to understand the differences between test disengagement and academic disengagement. Soland et al. (2019) proposed a theoretical model of the relationships among social-emotional competencies and engagement indicators, including growth mindset, self-efficacy, and self-management. However, there is significant overlap in their measurement, leading to potential misinterpretations of student disengagement.

Anderson et al. (2019) presented a theoretical model that examines how students' personal agency, namely their self-efficacy and perceived control, affects changes in their school engagement across the late middle school and early high school years. It further suggests that student involvement, in turn, has an impact on their academic achievement and attendance. While they offer strong conceptual insights, their technical applicability and scalability remain limited.

The authors examine current literature and empirical data to illustrate the many methods of fostering student agency in educational settings. Their discussions revolve around tactics such as tailored learning experiences, student-centred instructional approaches, and creating opportunities for students to have a say and make choices in the classroom. Moreover, the study examines the responsibilities of educators, administrators, and legislators in fostering student autonomy and establishing conducive learning environments. Anderson et al. (2019) emphasise the significance of teacher professional development, organisational structures that promote student input, and legislative efforts that empower students in their educational experience. It is arguable that the self-report assessment method has limited the generalisability of the proposed model, and it is not sensitive enough to detect changes in patterns associated with the high school transition.

Students are prone to discontinue their education either during the initial stages of enrolment, at an indeterminate point in their academic trajectory, or near the culmination of their schooling. Students' engagement can be influenced not only by their personal agency but also by their financial status (Murphy-Graham et al., 2020) and interpersonal relationships (Cristea et al., 2024). Therefore, there is a need to develop a comprehensive model that encompasses all relevant dimensions and can predict instances of school disengagement over time.

Another engagement-related study conducted by Järvinen and Tikkanen (2019) explores student disengagement in comprehensive schools in Turku, Southwest Finland. In line with background information on Finland's school system, the authors emphasize its commitment to equity, inclusivity, and individualized support for students by proposing a hypothetical behavioral engagement model.

It is found that all the school-level factors contribute to individual students' intrapersonal attitudes and experiences, which are then reflected in their behavioural engagement in schooling. Despite focusing on school-level factors, it is essential to develop a comprehensive model that can predict school disengagement over time and encompass all pertinent dimensions, aiming to identify students in the early stages of disengagement and enable timely interventions to sustain their engagement.

It is interesting to note that Bjugstad et al. (2023) have proposed a multidimensional model of social and environmental predictors of school engagement. This study investigated the impact of social determinants (nativity, economic adversity, and language) and environmental factors (community trauma, geographic location, and discrimination) on three aspects of school involvement (cognitive, behavioural, and relational) among Latino adolescents who were either first- or second-generation immigrants.

Although the authors integrated personal background and environmental factors into their prediction of school engagement, the study lacks exploration of how social position and environmental variables contribute to changes in school engagement. There is also potential for human bias in its data collection, arising from convenience sampling and self-report assessments. The authors also note that their model cannot make assumptions about causality or longitudinal trajectories of school engagement.

One of the most recent studies on school engagement, conducted by Katsantonis et al. (2024), proposed a longitudinal model examining how psychological and societal factors interact to explain why students in the UK choose to remain in school after completing compulsory schooling. This study examines the factors that strongly predict students' decision to continue their education, including parental education, childhood self-regulation, and school engagement. Although the present study used robust statistical and sampling methods, it is important to acknowledge that a short measure of school engagement was used due to the limited data available. Besides, the authors focus only on the significance of parental education, ethnicity, and gender, excluding the influence of cognitive ability and social class. Related studies in this area are summarised in Table 1.

Table 1. Comparison of existing studies on prediction of early school disengagement

Author	Year	Variables/predictors	Type of model	Limitation
Delen	2011	• Student's social integration • Parents' educational and financial background	Data-driven model	• Prediction using institutional data. • Dependency of a large dataset.
Subramainan et al.	2016	• Student behavioural issues • Motivation and participation influence teachers' and students' emotional states	Emotion-based model	• Focusing on the influence of student engagement on academic outcomes. • Do not exhibit heterogeneity of predictors.
Soland et al.	2019	• Growth mindset • Self-efficacy • Self-management	Theoretical model	• Prejudice of survey instruments (rapid guessing). • Do not warrant a causal interpretation.
Anderson et al.	2019	• Self-efficacy • Perceived control	Theoretical model	• Mono-method self-report assessment. • Not sensitive enough to detect a change in patterns.
Järvinen and Tikkanen	2019	• School size • School SES • School ethnicity • School investment • Teachers' attitude • Students' behaviour	Hypothetical model	• Only focus on behavioural engagement. • Fit to the Finnish local culture context. • Lack of comprehensiveness.

Author	Year	Variables/predictors	Type of model	Limitation
Bjugstad et al.	2023	• Social position • Promoting/inhibiting environments • Socio-political climate	Multidimensional model	• Bias in convenient sampling and self-report assessment. • Unable to make assumptions about the causality of school engagement.
Katsantonis et al.	2024	• Parental education • Ethnic majority • Gender	Hypothetical model	• Focusing on school-level transition. • Lack of cognitive ability and social class aspect. • Limited data collected.

Based on the current literature and the reviewed models, it is clear that existing frameworks for addressing school disengagement exhibit several significant limitations. These models often suffer from a narrow focus on individual aspects of engagement, which fails to account for the multifaceted nature of the issue. Additionally, there is a notable lack of attention to student diversity, resulting in models that do not adequately address the needs of heterogeneous groups. Many existing models are also not amenable to digital adaptation or automation, which limits their practical applicability in contemporary educational settings. Furthermore, reliance on predictive data analytics without a robust theoretical foundation can undermine the effectiveness of these models. There is also a lack of comprehensiveness in the selection of factors and predictor variables used in these models, which can lead to incomplete or inaccurate assessments of student disengagement.

With the rising use of predictive models, ethical issues have garnered heightened attention. Algorithmic bias, data privacy, and equity are essential issues, especially when models are used for heterogeneous student demographics. Predictive algorithms developed using biased datasets may unjustly categorise disadvantaged kids as at risk, thus perpetuating existing inequities. This is especially pertinent in the context of socio-economic inequalities, such as among the B40 student demographic in Malaysia. Xu et al. (2024) emphasise that even high-performing models can yield biased results when relying on self-reported or inadequate data. Moreover, the use of sensitive student data raises concerns about privacy and consent. Ethical implementation necessitates openness, accountability, and the integration of fairness-aware modelling tools. Notwithstanding these apprehensions, several current studies insufficiently address ethical considerations, thereby limiting their appeal to teachers and authorities.

In addition to technical performance, there is growing recognition of the need for human-centred AI in educational prediction systems. This methodology prioritizes usability, interpretability, and stakeholder endorsement. Numerous current models lack consideration of end users, making them difficult for instructors to understand and use effectively. Efficient solutions must provide actionable information, facilitate decision-making, and correspond with classroom reality. The integration of AI with conventional knowledge systems might improve contextual relevance and acceptability, especially in varied and globalized educational environments (Sharma, 2026). The insufficient emphasis on usability and stakeholder involvement remains a significant obstacle to adoption. Without trust and understanding, even the most precise models may not have a practical impact.

Current evidence indicates that existing approaches for addressing school disengagement have significant inadequacies when assessed across technical, usability, and acceptability aspects. Many models, from a technical standpoint, concentrate narrowly on single facets of interaction, neglecting its essentially multidimensional character. This constraint is exacerbated by inadequate factor selection and an insufficient number of predictor variables, resulting in imprecise or incomplete evaluations. Moreover, the growing dependence on predictive data analytics without a solid theoretical foundation undermines model resilience and interpretability. Numerous frameworks are inadequately intended for digital adaptation or automation, hence diminishing their scalability and efficacy in contemporary educational settings.

When it comes to usability, current models do not always provide the answers that educators and other stakeholders in educational institutions need. They are not easy to use in actual classrooms due to their complexity, lack of interpretability, and limited utility. Ethical issues are paramount with acceptance. Numerous parties are apprehensive and reluctant to use predictive systems owing to apprehensions of algorithmic bias, data privacy, and equality. Xu et al. (2024) highlighted that the use of self-reported or inadequate data might lead to distorted outcomes, even for high-performing models. Moreover, concerns around the use of private student data raise questions about consent, transparency, and accountability. Despite these challenges, insufficient attention to ethical issues in several current investigations is hindering broader institutional acceptance.

The development and evaluation of *MyBuddy* were guided by ethical principles to ensure that predictive analytics supported, rather than compromised, students' well-being. The dataset used in this study was obtained from a three-year intervention programme involving students from six secondary schools. Prior to participation, informed consent was obtained from the participating schools, students, and their parents or guardians (where applicable), authorising the use of the collected data for research and impact analysis. To safeguard participants' privacy, all student records were anonymised before analysis, and only authorised researchers had access to the research data. These measures ensured compliance with established ethical standards for educational research and protected the confidentiality of participating students.

The prediction model was designed as a decision-support tool rather than a diagnostic or labelling system. The risk classifications (low, medium, and high) were intended solely to assist school counsellors in identifying students who may require further assessment and support, rather than to determine a student's educational status or prescribe interventions automatically. Human oversight remained central throughout the evaluation process, with school counsellors reviewing the prediction results alongside their professional judgement, contextual knowledge, and existing student records before making any intervention decisions. This human-in-the-loop approach minimises the potential consequences of model misclassification and reduces the risk of inappropriate labelling or stigmatisation of students.

In addition, the selection of predictor variables was guided by established theoretical and empirical evidence rather than relying solely on algorithmic optimisation, thereby reducing the likelihood of biased decision-making. Unlike models that depend primarily on a limited set of demographic or academic variables, *MyBuddy* integrates multiple endogenous and exogenous factors associated with school disengagement to provide a more comprehensive and balanced assessment. Although no predictive model can completely eliminate algorithmic bias, continuous model refinement, validation using more representative datasets, and regular monitoring are essential to ensure fairness across diverse student populations. The comparatively lower prediction performance for the medium-risk category further highlights the need for ongoing evaluation before wider implementation. Collectively, these safeguards reinforce *MyBuddy* as a human-centred educational technology that promotes ethical, transparent, and responsible use of predictive analytics to support school counselling rather than replace professional judgement.

Given these shortcomings, there is a clear need for a new approach that addresses these gaps. This study aims to develop a more inclusive, adaptable, and comprehensive model to better identify and address the factors contributing to school disengagement. By addressing these critical issues, this study is important for developing a solution, thereby filling current gaps in the literature and practice.

To develop a comprehensive early prediction model, it is necessary to account for the exogenous and endogenous factors that contribute to school disengagement.

METHODS

The methodology adopted in this study was structured into six sequential phases to ensure a systematic and comprehensive evaluation of the proposed school disengagement predictive model implemented through the *MyBuddy* system. These phases were designed to guide the research process from model implementation and system development to data collection, testing, and analysis. The six phases involved are visually presented in Figure 1.

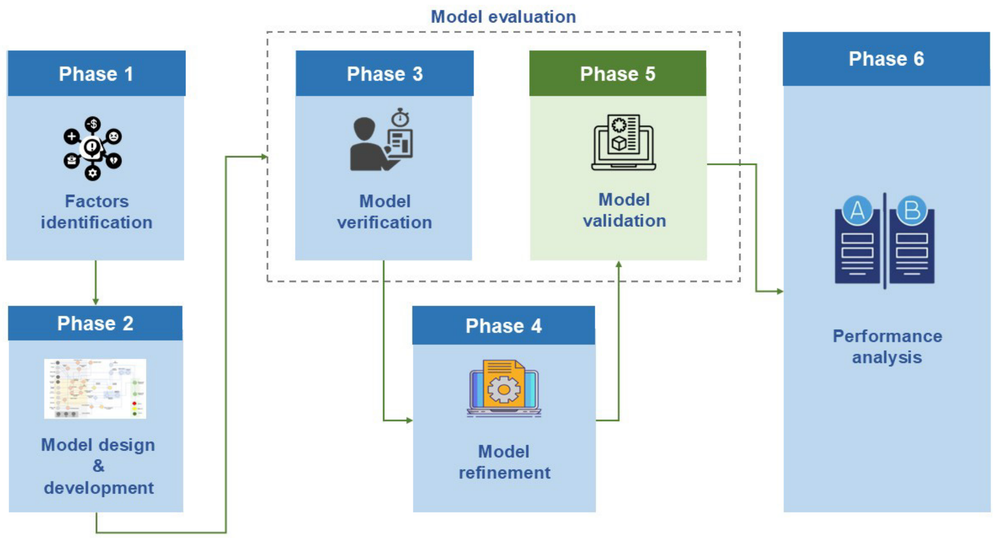


Figure 1. Research methodology

PHASE 1: FACTORS IDENTIFICATION

The identification of factors contributing to school disengagement was carried out through two systematic literature reviews (SLRs) conducted across six major academic databases. The first SLR utilised three primary scholarly databases: Scopus, Web of Science (WoS), and the Association for Computing Machinery (ACM) Digital Library. The involvement of these three reputable databases is to ensure comprehensive coverage of high-quality, peer-reviewed research. Scopus, recognised as one of the largest abstract and citation databases of scholarly literature, was complemented by WoS and ACM to capture multidisciplinary and computing-related studies. The second SLR expanded the scope by incorporating ProQuest, EBSCOhost, and Google Scholar, allowing broader access to educational and social science research.

Both SLRs followed a structured four-stage process comprising identification, screening, eligibility assessment, and data extraction and synthesis. During the identification stage, relevant keywords and search strings related to school disengagement, school dropout, and predictive factors were systematically applied. The retrieved studies were screened against predefined inclusion and exclusion criteria, followed by full-text assessment to determine eligibility. In the final stage, factors associated with school disengagement were extracted, synthesised, and consolidated.

This process identified 13 key factors, which were categorised into three principal domains: family-related, student-related, and environmental. These factors form the foundational components for the development of the proposed early prediction model for school disengagement. The list of the thirteen identified factors and their categories is visually represented in Figure 2.

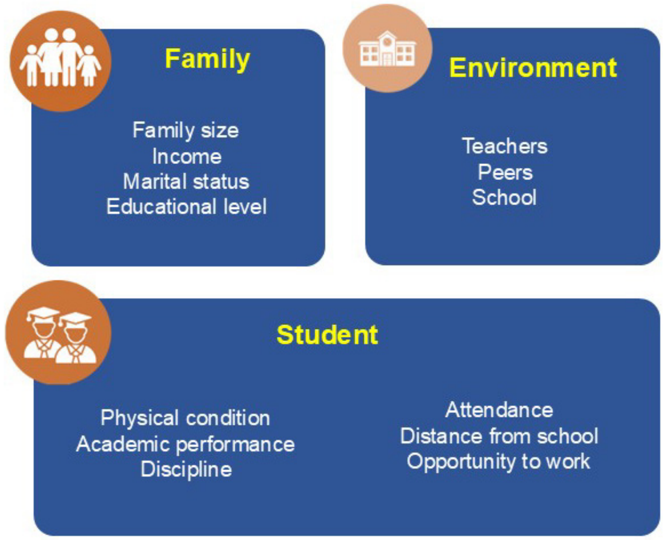


Figure 2. The thirteen identified factors

Phase 2: Model Design and Development

Based on the identification of 13 key predictors of school disengagement, a predictive model was developed using a network-oriented modelling approach. In this model, the 13 predictors serve as exogenous factors, each representing distinct yet interrelated dimensions that influence student disengagement. The network-oriented structure enables the modelling of complex interactions among predictors rather than treating them as isolated variables, thereby reflecting the multifactorial nature of disengagement observed in real-world educational settings. The constructed model is visually presented in Figure 3.

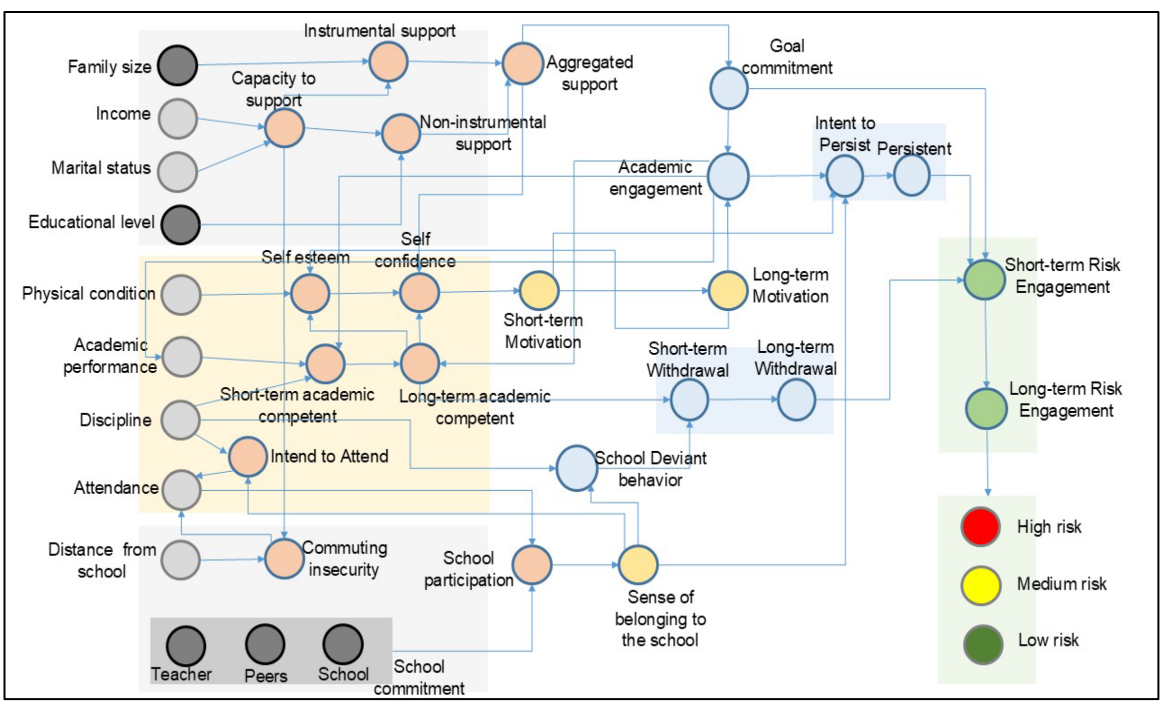


Figure 3. The proposed predictive model

Through interactions among these exogenous predictors, the model generates a set of instantaneous factors that capture the combined, dynamic influence of multiple risk indicators. These instantaneous factors are subsequently processed to produce the model's output, which categorises students into three disengagement risk levels: low, medium, and high. This tiered risk classification is designed to support counsellors in prioritising interventions and allocating resources more effectively, thereby reinforcing the model's role as a decision-support mechanism for early identification and preventive action.

Phase 3: Model Verification

Model verification was conducted through an expert review involving six experts, consistent with Nielsen's (1993) recommendation that five experts are generally sufficient to identify the majority of usability and design issues in a system. A purposive convenience sampling approach was employed to recruit experts who possessed relevant knowledge and practical experience in fields directly related to the development and implementation of *MyBuddy*. The panel consisted of specialists in educational psychology, school counselling, educational management, information and communication technology (ICT), and educational technology, ensuring a multidisciplinary evaluation of the proposed model. To be eligible, experts were required to have at least five years of professional or academic experience in their respective fields and demonstrate familiarity with student development, educational intervention, predictive analytics, or digital educational systems. Details of the experts are presented in Table 2.

Table 2. Demographics of experts

Experts	Field of expertise	Experience (year)
1	Education Psychologist	28
2	Domain Expert	13
3	ICT Expert	20
4	Domain Expert	15
5	ICT Expert	5
6	Education Psychologist	34

The experts were invited through professional networks and institutional collaborations and participated voluntarily in the model verification process. Each expert reviewed the proposed conceptual model, predictor variables, system workflow, and intervention framework using a structured evaluation instrument informed by the study objectives and the relevant literature on school disengagement and educational technology. The instrument consisted of items assessing the relevance, completeness, clarity, practicality, and suitability of the proposed model. Before its use, the instrument underwent face and content validation by senior researchers to ensure that the evaluation items adequately reflected the intended constructs. Feedback from the experts was subsequently incorporated into the refinement of the MyBuddy model before system development.

The primary objective of the verification process was to evaluate the correctness and quality of the predictive model using eight established dimensions of model quality as proposed by Batini et al. (2009): clarity, visibility, understandability, comprehensiveness, accuracy, effectiveness, evolutionary capacity, and flexibility. This structured evaluation enabled a rigorous assessment of the model's design, functionality, and adaptability, ensuring it meets both theoretical standards and practical requirements for application in school counselling contexts.

Phase 4: Model Refinement

Based on feedback from the expert verification process, the predictive model underwent a refinement phase to enhance its comprehensiveness and practical applicability. The improved model now comprises 14 contributing factors, representing an expansion from the 13 factors identified in the initial proposed model. This enhancement was achieved by including a new factor: the involvement of the Parents and Teachers Association (PTA).

The inclusion of PTA as an environmental factor acknowledges the critical role of family and community engagement in shaping student behaviour and learning outcomes. By explicitly incorporating this dimension, the refined model captures an important aspect of the educational ecosystem that was previously underrepresented. This not only strengthens the model's contextual relevance but also improves its explanatory and predictive capabilities. The refined model is illustrated in Figure 4, providing a clear representation of the updated structure and the interrelationships among all 14 contributing factors.

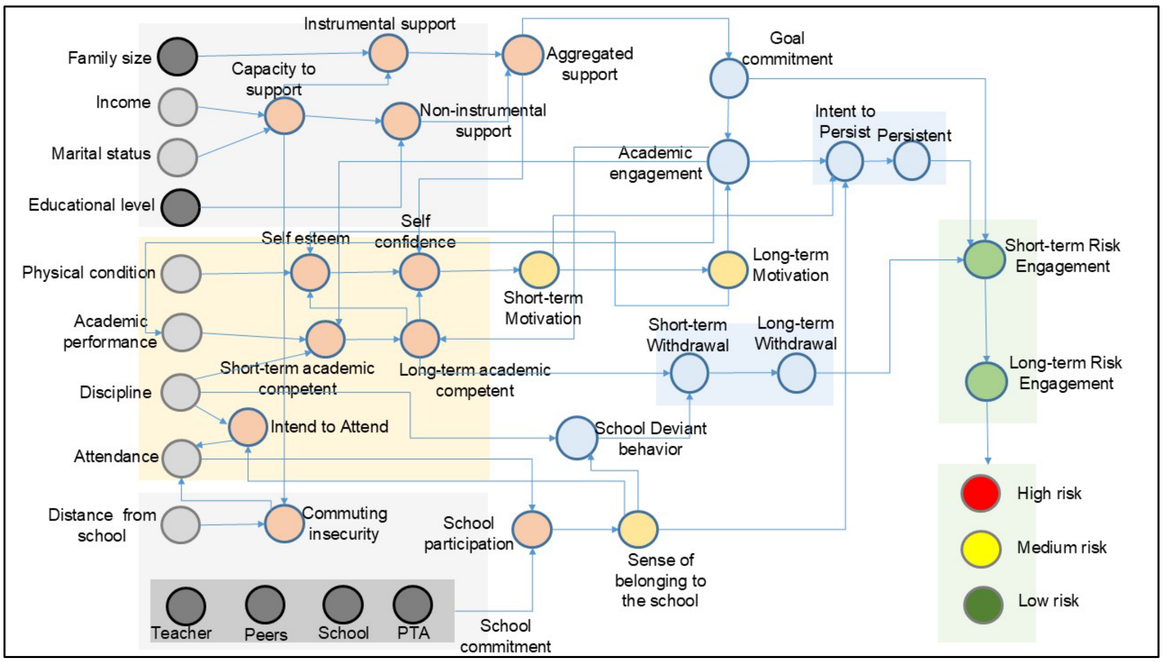


Figure 4. The refined predictive model

PHASE 5: MODEL VALIDATION

The main approaches used in model validation are prototyping and user experience tests, which focus on technical, usability, and acceptance dimensions. Prior to the user experience evaluation, *MyBuddy* prototype was designed and developed to implement the refined predictive model. It is available in both mobile and web environments and integrates the proposed model of early school disengagement to predict students at risk. *MyBuddy* is a translation of the model that incorporates all 14 predictive factors across three main entities of school dropout: student factors, family factors, and environmental factors. Family size, family income, marital status, and education level are four attributes of the family entity, while teachers, school friends, distance to school, school atmosphere, and involvement of the Parent-Teacher Association (PIBG) are five main attributes of the environment factor. For the student entity itself, the five main attributes that influence student involvement are the student's physical condition, academic achievement, disciplinary record, attendance record, and job opportunities in the surrounding area.

The main users of the *MyBuddy* application are all education stakeholders in Kedah: the Kedah State Education Department (JPNK), District Education Office (PPD), and school counsellors. *MyBuddy* was developed based on the requirements specifications obtained from several requirement gathering sessions with all target user groups. The requirements specifications for the MyBuddy application for JPNK officers, PPD officers, and school counsellors are listed in Tables 3, 4, and 5, respectively.

Table 3. Requirements specifications for JPNK officers

User: Kedah State Education Department (JPNK) Officer	
J1	Log in.
J2	View overall state Risk Report.
J3	View Risk Report by district under state control.
J4	View Risk Report of schools by district under state control.
J5	View list of students by district under state control.
J6	View individual student data details.
J7	View the list of school counsellors by district under state control.
J8	View individual counsellor profiles.
J9	View user profiles.
J10	Update user profiles, including name, password, and phone number.
J11	Log out.

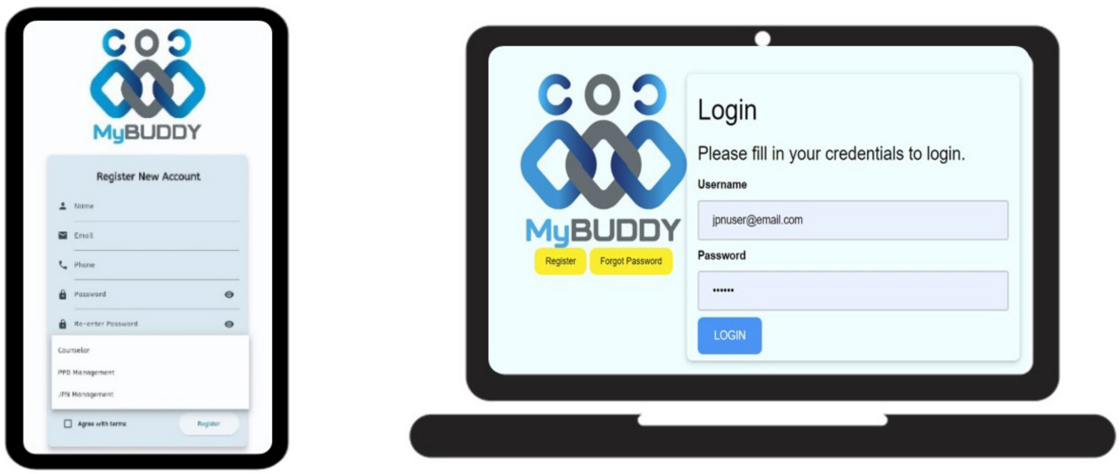
Table 4. Requirements specifications for PPD officers

User: District Education Office (PPD) officer	
D1	Log in.
D2	Displays overall district Risk Report.
D3	Displays ITL (Intention to Leave) Report for all schools under the control of the district.
D4	Displays list of students by school under the control of the district.
D5	Displays individual student data details.
D6	Displays list of counsellors for all schools under district control.
D7	Displays individual counsellor profiles.
D8	Displays user profiles.
D9	Update user profiles including name, password and phone number.
D10	Log out.

Table 5. Requirements specifications for school counsellors

User: School counsellors	
C1	Log in.
C2	Upload student data in bulk.
C3	Upload new student data individually.
C4	View list of students by school.
C5	View individual student data details.
C6	View list of student risk predictions.
C7	Edit individual student data.
C8	Print a list of student risk predictions.
C9	View the overall Risk Report for own school.
C10	Displays user profiles.
C11	Update user profiles, including name, password, and phone number.
C12	Log out.

The development of *MyBuddy* was carried out in both mobile and web environments, based on predefined requirements, to support its intended users and operational contexts. The mobile version was developed using Flutter, enabling cross-platform compatibility and facilitating on-the-go use among school counsellors, who require flexible, timely access during school-based activities. In parallel, a web-based version was developed specifically for administrative use within State Education Departments (JPN) and District Education Offices (PPD) to support centralised monitoring, data management, and decision-making. Both versions were designed with role-specific functionalities and interfaces to ensure usability and efficiency. The interfaces of the mobile and web versions are illustrated in Figure 5(a) and Figure 5(b), respectively.



(a) (b)

Figure 5. The interfaces of the mobile and web versions

The primary function of *MyBuddy* is to assess the level of school disengagement risk among secondary school students. The prototype is designed to operate as a decision-support tool, functioning like a calculator to compute a disengagement risk score based on predefined inputs. School counsellors are required to enter values corresponding to the 14 identified predictive factors, along with relevant student demographic information, to generate an overall risk assessment. This approach enables systematic and consistent evaluation of disengagement risk to support early identification and intervention. The interfaces of this function are visually presented in Figure 6.

Based on the values, *MyBuddy* computes and communicates three distinct levels of school disengagement risk, which are visually encoded using a colour-coded scheme to support rapid perception and reduce cognitive load among users. Upon completion of data entry, the calculated risk level is immediately displayed, as shown in Figure 7. A red indicator denotes a high risk of disengagement, signalling the need for immediate attention and targeted intervention. A yellow indicator represents a moderate level of risk, prompting closer monitoring and preventive support, while a green indicator indicates a low risk of disengagement and minimal immediate concern.

The use of colour-based risk cues aligns with established human factors principles, particularly in supporting situational awareness, visual salience, and efficient decision-making. By enabling school counsellors to briefly assess risk levels without extensive cognitive processing, the interface facilitates the prioritisation of cases and timely responses. This design approach enhances usability and operational efficiency in real-world school settings.

MyBuddy was subsequently evaluated across multiple dimensions, namely technical performance, usability, and user acceptance, with each evaluation conducted in separate sessions involving different groups of participants according to their expertise and roles. The technical evaluation involved 27 information technology (IT) experts recruited voluntarily through an open call for system testers, disseminated via academic and professional networks. Participants were selected through purposive convenience sampling and were required to have at least 5 years of professional or academic experience in information technology, software engineering, computer science, or related disciplines. The panel comprised experts from four higher education institutions, ensuring a diverse range of technical perspectives in assessing the functionality, reliability, and technical quality of the *MyBuddy* system.

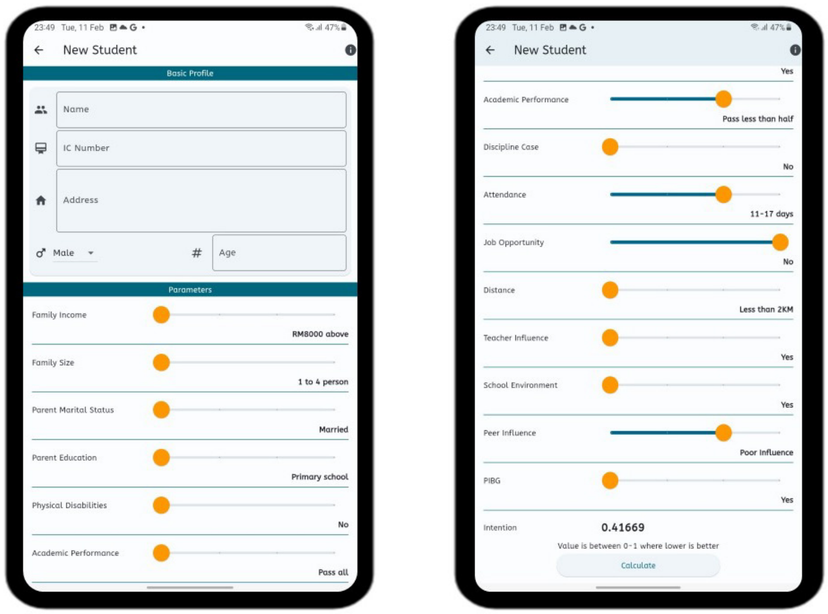


Figure 6. The interfaces of *MyBuddy* calculator

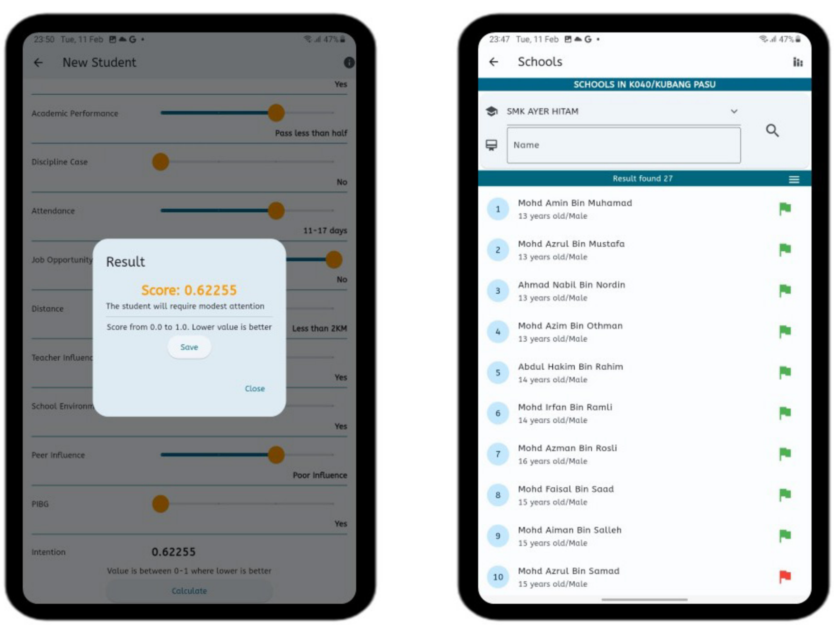


Figure 7. The interfaces of *MyBuddy* risk results

The usability and user acceptance evaluation involved 27 technical testers, comprising school counsellors and officers from the State Education Department (JPN). These participants were purposively selected for their direct involvement in student welfare, counselling services, and educational management, as they represent the intended end users of MyBuddy in real-world school settings. Their participation enabled the evaluation to focus not only on system usability but also on the practicality, usefulness, and suitability of the proposed model for supporting early identification and intervention of students at risk of school disengagement. The evaluation instruments for both technical and usability assessments were developed based on established software quality and technology acceptance constructs and were reviewed by the research team before deployment to ensure clarity, relevance, and suitability for the respective participant groups. The evaluation procedures are presented in Phase 6 while its corresponding findings for each assessment are presented in Results and Discussions.

Phase 6: Performance Analysis

To evaluate the proposed model implemented in MyBuddy, a performance analysis was conducted using system-generated data. Two school counsellors and 50 students from two schools participated in the study. The counsellors manually assessed and predicted each student's risk level, and the same predictions were then generated using *MyBuddy*. The results from both methods were subsequently compared to assess the model's accuracy and effectiveness.

Results and Discussions

This section presents the findings of the study and provides a comprehensive discussion of the results. The analysis is structured into three key areas: Technical Testing Results, which evaluate the functionality and performance of the *MyBuddy* system; Usability and Acceptance Testing, which assesses the user experience, ease of use, and overall satisfaction of counsellors interacting with the application; and Comparative Analysis, which examines the alignment between *MyBuddy's* predictions and manual assessments conducted by counsellors. These discussions provide a holistic understanding of the system's effectiveness, reliability, and potential for practical implementation in school counselling contexts.

Technical Testing Results

A thorough technical testing session was conducted, involving a diverse cohort of IT professionals and technical specialists from various institutions. The main goal of this session was to thoroughly assess and confirm the quality and technical validity of the MyBuddy prototype. The review approach was centred on three essential dimensions: design and layout, interactions and simplicity, and functions and performance.

In the first dimension, design and layout, the testers assessed the system's visual coherence, navigational organisation, aesthetic consistency, and adherence to user interface (UI) design standards. The second dimension, interactivity and simplicity, focused on how easy the interface was to use and how clear the procedures were. It also looked at how responsive the interface components were and how well they helped users do important tasks without making things too complicated. Third, the functionality and performance component looked at operational reliability, processing efficiency, and system responsiveness. It showed that all of the important elements worked as predicted in a variety of technological environments and workloads.

Design and layout dimension

Eight items were evaluated on a 5-point Likert scale for the design and layout dimension. The items are as shown in Table 6. The results in Figure 8 show that the majority of testers (59.3%) gave the maximum possible rating for Item 1, which aligns with the prototype's layout. However, 25.9% of testers felt neutral on the layout arrangement, 7.4% strongly agreed, while another 7.4% disagreed. This suggests that the majority of users perceive the interface to be simple to use and that items are positioned appropriately. For Item 2, 48.1% of testers agreed with the organisation, 25.9% were neutral, and 22.2% strongly agreed. Small parts of testers responded with disagreement (3.7%) and strongly disagreed (0%). This indicates that testers, on the whole, believe the content structure is understandable; nonetheless, there is still room for improvement in how information is presented.

Table 6. The items in the design and layout dimensions

No.	Items
1	The placement and alignment of buttons, icons, and other UI elements are intuitive and easy to interact with.
2	The organisation of the information presented is clear.
3	Design elements throughout the app are consistent to maintain a cohesive visual experience.
4	The app adapts to different screen sizes and orientations, ensuring it remains usable and visually appealing.
5	Colour choices and use of visuals are appropriate, visually appealing, and do not hinder usability.
6	Text (including font choices, size, and spacing) is readable.
7	Typography is consistent throughout the app.
8	Overall, the look of the interface is pleasant to the eyes.

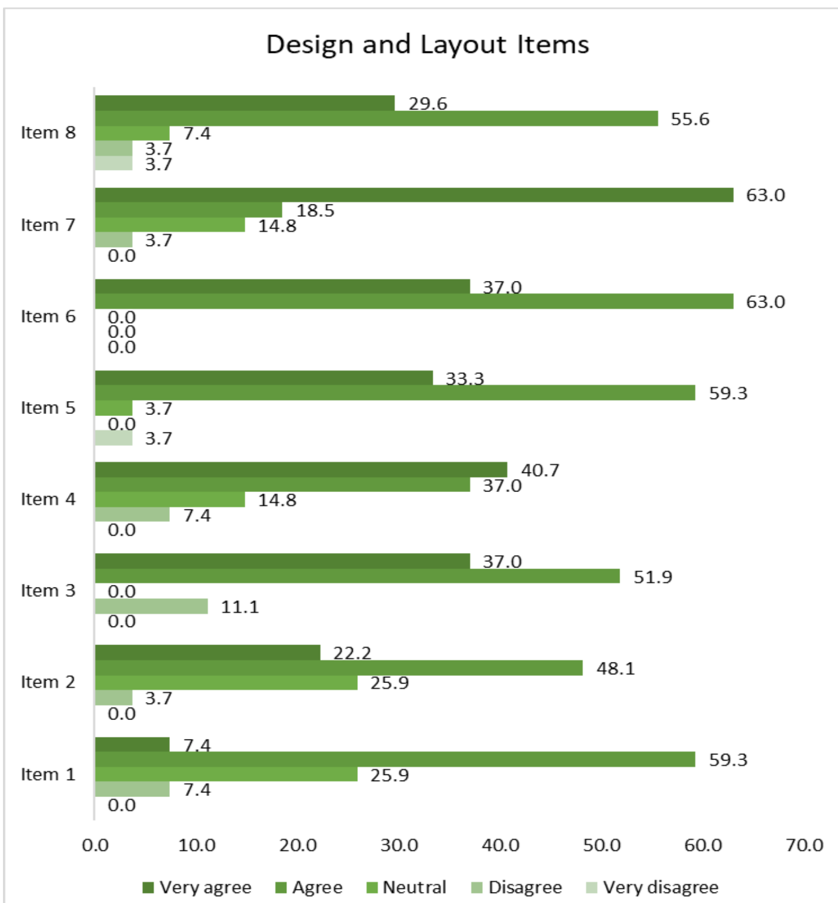


Figure 8. Design and layout itemised results

Meanwhile, 51.9% of respondents agreed, while 37% strongly agreed with Item 3, reflecting that the prototype maintained a consistent visual and stylistic design. Only 11.1% disagreed, and none strongly disagreed or remained neutral. This indicates a strong level of satisfaction among users regarding the uniformity and coherence of the design elements throughout the prototype. Regarding Item 4, 40.7% of testers strongly agreed, with 37% agreeing that the program adjusts adequately to different screen sizes. This demonstrates that more than three-quarters of respondents considered the design highly responsive. A smaller percentage of individuals were indifferent (14.8%), with just a few disagreeing (7.4%) and none strongly disagreeing.

As for Item 5, the majority of testers agreed (59.3%) or strongly agreed (33.3%) that the prototype's design was visually appealing in terms of colour and overall appearance. None disagreed, and only a tiny percentage (3.7%) expressed indifference or strong disagreement. This suggests that although some testers remained indifferent or dissatisfied, most found the colour scheme and overall visual presentation attractive. The high agreement rate indicates that the colours were used well to create a visually appealing and captivating design.

Positive feedback was abundant regarding the readability of the content (Item 6). There were no disagreements or neutral responses, as all testers agreed (63%) or strongly agreed (37%) that the material was simple to understand. This consensus of favourable comments demonstrates that the design was successful in achieving outstanding legibility and clarity. It also suggests that elements such as font selection, size, and colour contrast were well balanced and effective in increasing readability.

The responses to typographic consistency were similarly quite positive, but somewhat more varied than readability. The majority (63%) strongly agreed, with 18.5% saying the typography was consistent, 14.8% indifferent, and 3.7% disagreeing. This shows that although the majority of respondents regarded the typography as consistent and harmonious, a small percentage identified inconsistencies in font styles, alignment, or spacing that should be improved further. Nonetheless, the overall impression was highly good for Item 7.

Upon assessing the visual appeal of the design (Item 8), a majority of testers concurred (55.6%) or strongly concurred (29.6%), indicating that the design was mostly aesthetically pleasing and comfortable. Nevertheless, a minority of respondents were neutral (7.4%) or expressed dissent (3.7% each for strongly disagree and disagree), suggesting that a small segment found the design somewhat less calming or perhaps visually overpowering. The findings indicate that while most participants deemed the design visually appealing, slight modifications in contrast, brightness, or spacing might improve overall visual comfort.

In general, the results indicate that the testers responded favourably to the prototype's design and layout. Most agreed or strongly agreed that the layout was straightforward and things were grouped logically, making the interface easy to use. Some testers advised clarifying the arrangement of information, but overall, it was well rated. Testers liked the colour scheme and visual appeal, finding it beautiful and interesting, and the text's readability was unanimously favourable, suggesting clear content. Although typography consistency and visual comfort were disputed, the prototype's design and layout were well-executed, user-friendly, and aesthetically pleasing, with only minor improvements needed to improve the user experience.

Interaction and simplicity dimension

A 5-point Likert scale was used to assess seven questions, all of which corresponded to the interaction and simplicity dimensions. The items are depicted in Table 7. The findings for the interactions and simplicity dimensions reveal a generally positive view of the prototype's practicality, as depicted in Figure 9. For simplicity of use, the responses clearly demonstrate a high level of satisfaction. Almost half of the testers (48.1%) agreed, and an additional 40.7% strongly agreed that the program is user-friendly, while just 11.1% were neutral and none disagreed. The largely favourable feedback indicates that the prototype achieved a high level of intuitiveness, enabling users to perform tasks with minimal effort and learning. The interface seems to be simple and intuitive, which is essential for enhancing accessibility for both novice and seasoned users. The lack of dissent further corroborates that the overall design effectively reduces complexity and ambiguity.

Table 7. The items in interaction and simplicity dimensions

No	Items
1	It is simple to use this application.
2	It is easy to find the information needed.
3	The flow and navigation of the application are clear to ensure users can easily move between screens without confusion.
4	Navigation labels and icons are clear.
5	Responsiveness of touch gestures (swiping, tapping, pinching) is smooth and intuitive.
6	Loading times and responsiveness of the app are optimised for a smooth user experience.
7	Error messages and notifications are clear and helpful.

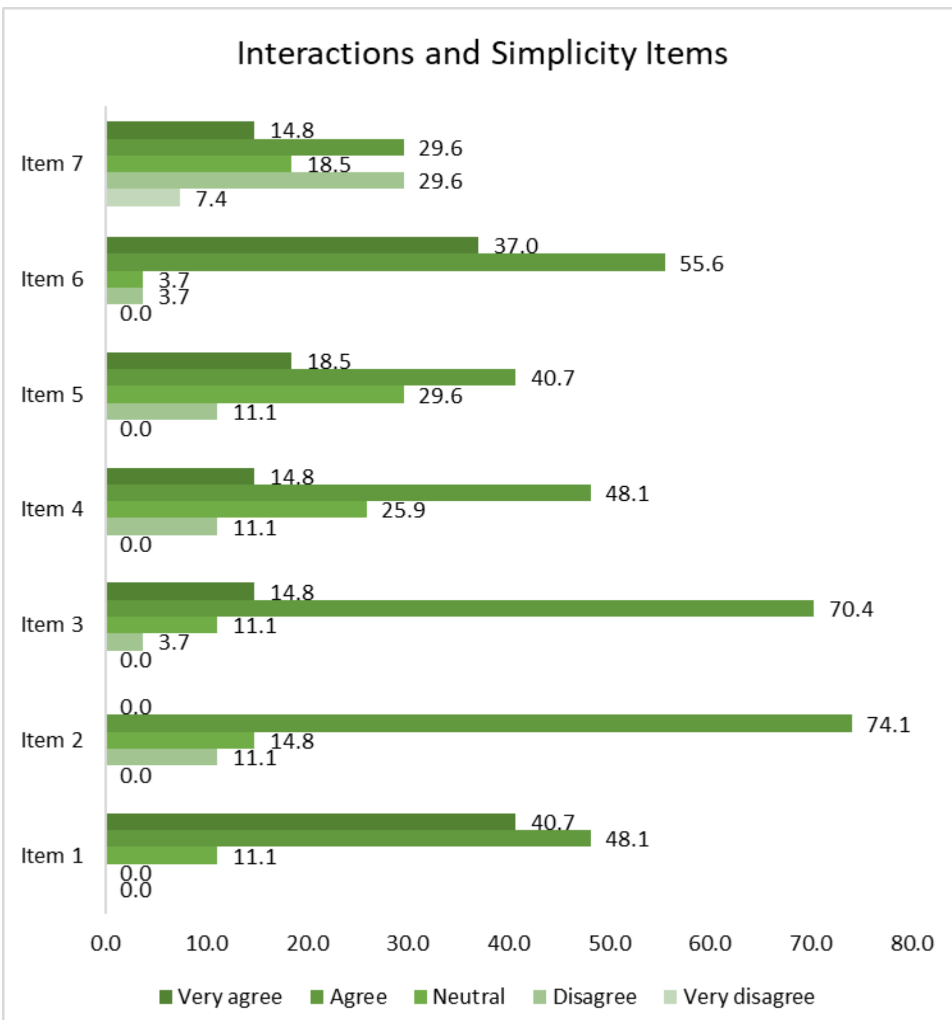


Figure 9. Interactions and simplicity itemised results

In terms of information retrieval, the outcomes were comparably positive, although slightly more diverse. A large proportion of testers (74.1%) agreed that the information within the application was easily accessible, suggesting that the information architecture and content arrangement were mostly well organised. Nonetheless, 11.1% expressed disagreement and 14.8% remained neutral, suggesting that a modest segment of users may have had slight difficulty locating or accessing specific information.

In evaluating the clarity of flow and navigation, testers reacted favourably, with 70.4% expressing agreement and 14.8% indicating strong agreement, underscoring that most users could transition between screens and tasks without confusion. Only 3.7% expressed disagreement, and 11.1% remained neutral, suggesting that the navigation structure is mostly functional, but some users may have encountered some confusion or ambiguous transitions between parts.

As for the navigation icons and labels (navigation labels and icons are obvious), opinions were more polarised. Of the testers, 48.1% agreed, 14.8% strongly agreed, 25.9% were neutral, and 11.1% disagreed. The replies indicate that although most users comprehended the navigation labels and icons, there may be discrepancies or ambiguities in the visual symbols or language used. These replies presumably indicate individual variations in familiarity rather than deficiencies in design. The findings demonstrate that the *MyBuddy* prototype employs clear, well-organised navigation icons, facilitating a user-friendly, intuitive experience that enables users to engage with the app confidently and efficiently.

The findings on the responsiveness of touch were mostly favourable, indicating that testers were primarily content with the interactive performance of the *MyBuddy* prototype. A substantial majority, 59.3% of testers, agreed or strongly concurred that the touch gestures operated seamlessly and intuitively, suggesting that the app delivers a natural and responsive interaction experience. The remaining 29.6% of indifferent and 11.1% of dissenting comments indicate that, while some testers may have encountered minor discrepancies, the overall feedback demonstrates robust functioning. The results indicate that *MyBuddy's* touch-based controls are efficient and intuitive, enabling users to browse and engage with the program seamlessly.

The performance-related comments about loading times and responsiveness were notably positive. A majority of testers (55.6% agreed and 37% strongly agreed) reported that *MyBuddy's* loading times were optimised, resulting in a seamless experience. Merely 3.7% of respondents expressed neutrality, while an equivalent 3.7% voiced disagreement. This indicates that the prototype is technically optimised, providing a snappy interface that reduces delays and improves customer happiness. Smooth transitions and rapid reaction times are essential for sustaining interest, and *MyBuddy* seems to excel in this aspect.

The findings for error messages (alerts are clear and helpful) were mostly positive, indicating that most testers valued the clarity and utility of *MyBuddy's* system feedback. A total of 44.4% of testers agreed or strongly concurred that the alerts and error messages were informative and beneficial in directing their activities. This indicates that the prototype effectively conveys essential information and helps users understand system responses. A minority of individuals expressed indifferent or divergent opinions, which presumably reflect personal preferences rather than substantive design concerns. The data indicates that the prototype feedback mechanism effectively maintains user awareness and engagement.

In conclusion, the assessment of interactions and simplicity reveals that the *MyBuddy* prototype demonstrates very high performance in ease of use, navigation flow, and responsiveness. Testers appreciated the straightforward design and logical organisation, noting that it facilitates interaction that is both efficient and intuitive.

Functionality and performance dimension

A 5-point Likert scale was used to assess three questions, all of which corresponded to the *functionality and performance* dimension (Table 8).

Table 8. Items in functionality and performance dimensions

No	Items
1	Features and functionality work as expected and according to the requirements.
2	The app handles various inputs and interactions correctly.
3	Response time, load time, and overall performance are consistent under different device configurations.

Findings from the functionality and performance dimension of the *MyBuddy* prototype indicate mostly favourable user feedback, with most testers recognising that the application effectively delivers its intended functionality and maintains consistent responsiveness across devices, as illustrated in Figure 10.

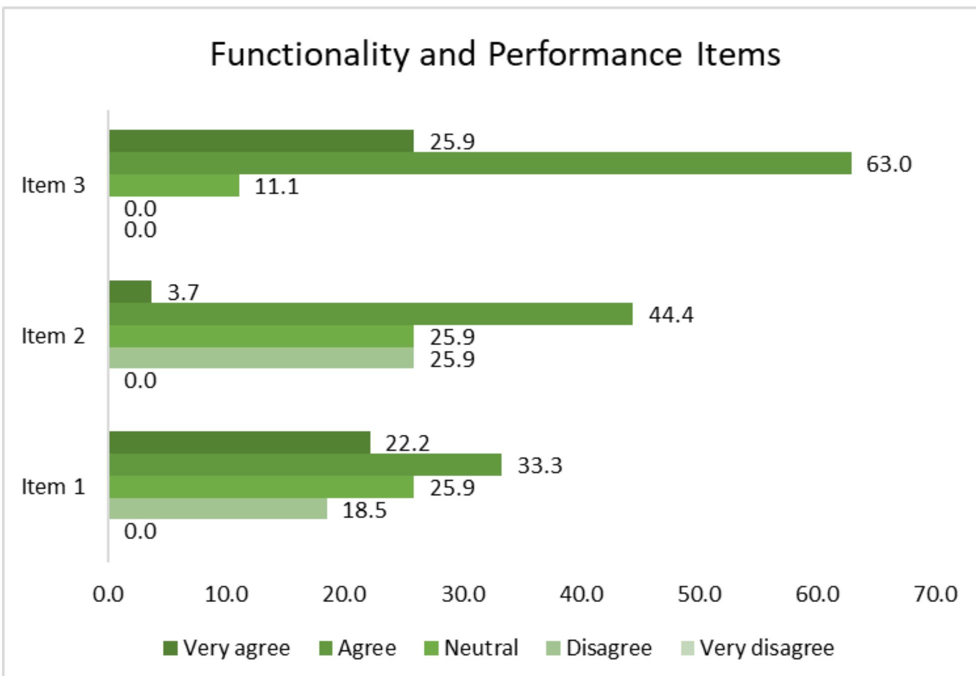


Figure 10. Functionality and performance itemized results

Regarding the reliability of features and functionality (features and functions perform as anticipated and in accordance with the criteria), the responses indicate a generally positive view: 25.9% of testers remained neutral, and 18.5% disagreed with the statement that the prototype's features functioned correctly and met expectations. The majority of testers either agreed (33.3%) or strongly agreed (22.2%) with this statement. This suggests that most users consider MyBuddy's key features dependable and effective. However, only a minority of users may have encountered minor anomalies or partial feature replies. Despite this, the significant percentage of testers who agreed with the statement suggests that the prototype meets users' expectations.

The responses were significantly more split with regard to accuracy in handling inputs and interactions (the app demonstrates proper handling of a variety of inputs and interactions). A total of 51.8%

of testers were either indifferent (25.9%) or disagreed (25.9%), with 44.4% agreeing and 3.7% strongly agreeing. Over half of users believed that *MyBuddy* reacted adequately to a variety of user inputs. These findings indicate that the prototype performs well in most circumstances.

Item 3, which states that response time, load time, and overall performance are constant across a variety of device configurations, garnered the most favourable responses. However, only 11.1% of testers were indifferent, and none disagreed with the statement. A substantial majority of testers either agreed (63.0%) or strongly agreed (25.9%). This is evidence that testers performed smoothly and reliably regardless of the device they used, the screen size, or their hardware capabilities. The fact that there are no negative responses demonstrates that *MyBuddy's* performance has been finely tuned, that it processes information well, and that it responds quickly.

The analysis of functionality and performance dimensions indicates that the *MyBuddy* prototype successfully fulfils its planned functionality, manages user interactions proficiently, and maintains consistent performance across devices. Although several users identified small areas for improvement regarding its responsiveness to diverse inputs, the general feedback suggests that *MyBuddy* is a solid, dependable, and well-optimised program.

After concluding technical testing to validate the prototype's functionality, performance, and reliability, the next phase focuses on evaluating its effectiveness in meeting user requirements in real-world settings. Usability and acceptance testing complement technical validation by assessing the model's intuitiveness, user satisfaction, and overall acceptance among potential users.

Usability and Acceptance Testing

A thorough usability and acceptance testing session was performed with 27 respondents, including school counsellors, district officials from the District Education Office (PPD), and stakeholders from the State Education Office (JPN). Figure 11 presents the demographic analysis of the respondents by role: 59.3% are PPD staff, 22.2% are school counsellors, and 18.5% are JPN admins.

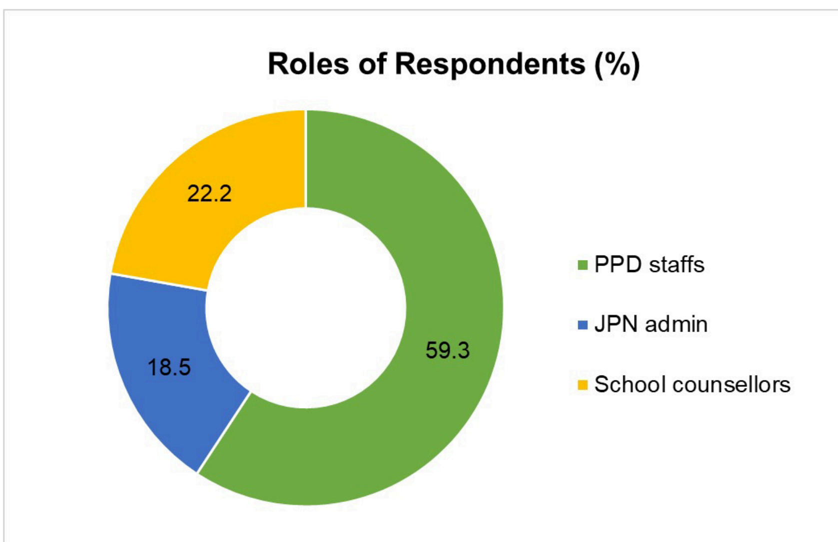


Figure 11. Role of testers

The main aim of this section is to systematically assess and confirm the usability and workability of the proposed model that underpins the tangible product. The evaluation procedure was organized around six essential dimensions: design and layout, usability, utility, learnability, functionality, and performance and satisfaction. The results are illustrated in Figure 12.

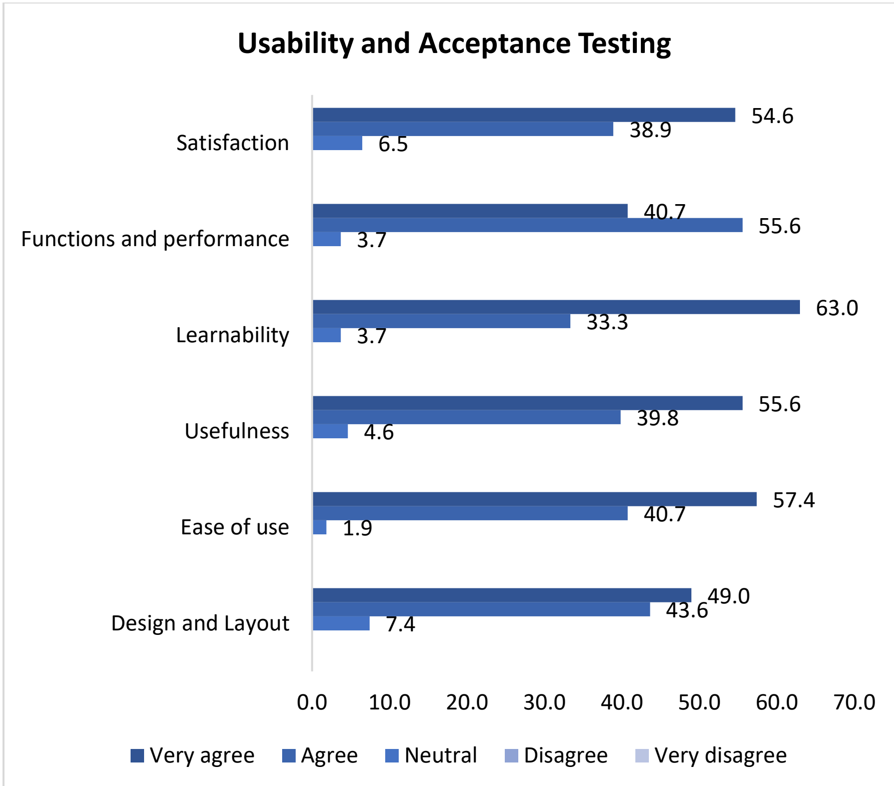


Figure 12. Six dimensions of usability and acceptance testing results

The majority of participants offered positive feedback on the Design and Layout category, with over 93% agreeing or strongly agreeing with most statements. This indicates that the system's visual organisation, structure, and general aesthetic are attractive to users and come naturally to them. Similarly, the Ease of Use category received a relatively high score, with almost all respondents admitting that they found MyBuddy simple to use. Consequently, this indicates that users can navigate the interface without unnecessary confusion or complexity.

Both the Learnability and Usefulness dimensions are highly rated, indicating that users perceive the prototype as beneficial and can rapidly comprehend how to use it. Based on these findings, the MyBuddy application can provide users with the assistance they need to accomplish their objectives while reducing the time required to learn to use the system.

Users' perceptions of the prototype's functionality and ability to provide its intended features are overwhelmingly good. As 55.6% of respondents agreed, and 40.7% strongly agreed, this indicates that 96.3% generally think the prototype performs as expected and that its features operate well. It is significant that none of the users objected or strongly disagreed, and only 3.7% opted for neutral. According to these results, the prototype functions proficiently in accordance with the model underpinning its formulation. The prototype successfully implements the model's concepts, ensuring that all essential functions and features work as intended, as evidenced by the high levels of agreement among respondents. The concordance between model and prototype performance confirms that the conceptual framework has been successfully translated into a functional system capable of predicting students' risk of engagement.

The satisfaction findings indicate that users are very satisfied with their entire experience using the *MyBuddy* application. A total of 93.5% of respondents indicated satisfaction, with 38.9% agreeing and 54.6% strongly agreeing. Merely 6.5% chose neutral, and none expressed unhappiness. This pattern indicates that users not only value certain elements of the system, such as design, usability, and performance, but also have a favourable overall perception of the system. The high satisfaction rating indicates that the system effectively fulfils users' expectations, delivering a seamless, efficient, and pleasurable experience. Users are likely to feel assured in using the system and see it as beneficial to their jobs or goals. It can be concluded that the *MyBuddy* prototype meets users' expectations and aligns with the goals specified in the underlying development model.

The usability and acceptance findings provide compelling evidence that the *MyBuddy* prototype is both user-friendly and practically valuable to its intended users, including counsellors and education officers. High ratings across usability, learnability, and satisfaction indicate not only ease of use but also strong perceived relevance to professional tasks. These results address a key gap in existing predictive systems, where limited real-world adoption often undermines technical advancements. In contrast, the *MyBuddy* prototype demonstrates strong behavioural acceptance, reflected in users' ability to quickly learn the system, recognise its value, and engage with it meaningfully.

Collectively, these findings suggest that *MyBuddy* extends beyond technical feasibility to practical applicability, positioning it as a viable support tool for deployment in counselling contexts. More importantly, the results reinforce that user acceptance is a critical determinant of successful implementation, highlighting the system's readiness for real-world integration.

Performance Analysis

This analysis used data from 50 students with diverse educational backgrounds and grade levels. The proposed School Disengagement Early Prediction Model was used to generate the model prediction. The model predicted the early signs of each student's disengagement by using a combination of student data indicators (14 factors, including Parents-Teachers Association, as suggested by the expert). The model's output was presented in the same categorical format as the counsellor's appraisal, which enabled a direct comparison between human judgment and model prediction.

To ensure that human and model evaluations were consistent, the risk associated with school disengagement was categorised into three levels: low, medium, and high. The result of the comparative analysis is shown in Table 9.

Table 9. Confusion matrix of human judgement and model predictions

Model predictions / Human judgement	Predicted low risk	Predicted medium risk	Predicted high risk
Low risk	6	1	1
Medium risk	7	5	2
High risk	4	9	15

The diagonal values in the confusion matrix (6, 5, and 15) represent instances that were correctly classified by the model, in which the predicted risk levels aligned with the counsellors' assessments. In contrast, off-diagonal values indicate misclassifications. Of the 50 participants evaluated, 26 were correctly classified, while 24 were misclassified. Based on the confusion matrix, the overall accuracy of the proposed model is calculated to be 52%, as shown in Equation (1).

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} = \frac{26}{50} * 100 = 52\% \quad (1)$$

Standard performance metrics, including accuracy, precision, recall, and F1-score, were calculated to assess the model's performance. For each level of risk, precision is calculated using the formula in Equation (2), and recall is calculated using Equation (3). The value of F1 is calculated using Equation (4).

$$Precision = \frac{TP_i}{TP_i + FP_i} \tag{2}$$

$$Recall = \frac{TP_i}{TP_i + FN_i} \tag{3}$$

$$F1\ score = 2\ x \frac{Precision_i\ x\ Recall_i}{Precision_i + Recall_i} \tag{4}$$

Where TP_i refers to true positive (diagonal entry), FP_i refers to instances that the model predicts as belonging to a given category when the actual category is different (obtained from the prediction column excluding the diagonal), FN_i refers to instances that actually belong to a given category but are predicted as another category (obtained from the actual row, excluding the diagonal. The results are depicted in Table 10.

Table 10. Precision, recall, and F1 score by risk level

Risk level	Precision	Recall	F1 score
Low (1)	6/(6+7+4) = **0.35**	6/(6+1+1) = **0.75**	**0.48**
Medium (2)	5/(5+1+9) = **0.33**	5/(5+7+2) = **0.36**	**0.34**
High (3)	15/(15+1+2) = **0.83**	15/(15+4+9) = **0.54**	**0.65**
Macro average	**0.50**	**0.55**	**0.49**

The proposed *MyBuddy* model demonstrated its strongest performance in identifying students in the high-risk disengagement group, achieving a precision of 0.83, indicating that 83% of students predicted as high risk were correctly classified. This finding is particularly important because the primary objective of school disengagement prediction is not merely to maximise overall classification accuracy, but to accurately identify students who require immediate intervention. In contrast, the medium-risk group recorded the lowest precision and recall, suggesting that students in this category share behavioural and demographic characteristics with both the low-risk and high-risk groups. Such overlap is commonly reported in multi-class educational prediction problems, where transitional risk profiles are inherently more difficult to distinguish.

Although the overall classification accuracy of 52% appears modest, the results should be interpreted in the context of the model's intended application. Unlike conventional predictive models that primarily emphasise statistical performance, *MyBuddy* was designed as a decision-support tool for school counsellors. Its high precision for the high-risk category minimizes false-positive cases, enabling counsellors to prioritise students who are most likely to disengage from school. This targeted capability is particularly valuable in schools where counselling personnel and intervention resources are limited. Consequently, the practical value of *MyBuddy* lies in supporting early identification and prioritisation rather than in replacing professional judgement or functioning as a fully automated prediction system.

Compared to previous school disengagement prediction models (Table 1), *MyBuddy* offers several notable improvements. Existing studies have predominantly focused on maximising predictive accuracy through machine learning techniques while offering limited support for practical implementation in schools. In contrast, *MyBuddy* integrates predictive analytics with a human-centred intervention approach by incorporating 14 validated disengagement predictors into a mobile- and web-based platform specifically designed for school counsellors. Rather than presenting prediction results alone, the system categorises students into low-risk, medium-risk, and high-risk levels using an intuitive colour-coded interface, enabling counsellors to rapidly identify priority cases and plan appropriate interventions. This combination of predictive capability, usability, and practitioner-oriented design distinguishes *MyBuddy* from many previous prediction models that remain largely research prototypes lacking direct operational support for counselling practice.

The findings also contribute to the growing field of predictive analytics in education by demonstrating that prediction models should be evaluated based on their practical usefulness in supporting educational decision-making rather than solely on overall accuracy. For educational settings, particularly those involving student welfare and counselling, accurately identifying high-risk students is often more valuable than achieving marginal improvements in overall classification performance. The high precision achieved for the high-risk group suggests that *MyBuddy* can function as an effective early warning system, allowing schools to allocate intervention resources more efficiently and reduce the likelihood of overlooking vulnerable students.

From the perspective of school counselling, the findings demonstrate the potential of integrating artificial intelligence and predictive analytics into routine counselling practices. *MyBuddy* provides counsellors with evidence-based insights that complement, rather than replace, professional assessment. The system enables counsellors to monitor students systematically, identify emerging disengagement risks at an earlier stage, and implement timely intervention strategies. Such a human-centred approach supports more proactive counselling services while maintaining the essential role of counsellors in interpreting prediction results within the broader context of each student's circumstances.

Finally, the study contributes to the development of human-centred educational technology by demonstrating that the effectiveness of educational prediction systems depends not only on algorithmic performance but also on usability, accessibility, and alignment with users' real-world workflows. The integration of predictive analytics within an intuitive mobile and web-based platform increases the practicality and adoption potential of the proposed system in schools. Nevertheless, the relatively lower performance for the medium-risk group indicates that further refinement is required. Future research should investigate advanced machine learning techniques, larger, more balanced datasets, and additional behavioural or contextual predictors to improve discrimination among students at moderate risk of disengagement while preserving the model's strong capability in identifying high-risk students.

CONCLUSIONS

This study provided a comprehensive evaluation of a school disengagement predictive model implemented through the *MyBuddy* system, examining its effectiveness across technical performance, usability, and user acceptance dimensions. From a technical perspective, the model demonstrated a moderate level of predictive accuracy, suggesting its potential as a decision-support tool for school counsellors in the early identification of students at risk of disengagement. Although the model is not intended to replace professional judgment, its ability to support timely intervention highlights its practical value in school counselling contexts.

The usability and acceptance findings revealed strong positive responses from counsellors, particularly regarding ease of use, interface clarity, and suitability for a mobile-based, on-the-go application. These outcomes emphasise the importance of user-centred design in educational technologies and suggest that *MyBuddy* is well positioned for integration into routine counselling practices. High acceptance levels further indicate readiness for real-world adoption, especially in resource-constrained school environments where efficient tools are essential. Strong positive responses from counsellors regarding ease of use, clarity, and mobile accessibility suggest that *MyBuddy* is not only functional but also operationally viable in real-world contexts, particularly in environments with limited time and resources. These findings underscore that adoption in practice depends as much on human-centred design as on algorithmic accuracy, an aspect often underemphasized in prior research on predictive modelling.

From a scholarly perspective, this study contributes to the existing body of research in two ways. First, it advances current work on school disengagement prediction by integrating multidimensional indicators into an applied predictive framework that extends beyond purely academic performance metrics, addressing a commonly identified limitation in earlier studies. Second, it addresses a gap in the literature by combining technical evaluation with systematic assessments of usability and acceptance, thereby bridging the divide between model development and real-world implementation. In contrast to prior studies that primarily report predictive accuracy, this research demonstrates the importance of evaluating both system effectiveness and user readiness as interconnected factors.

Importantly, the outcomes of this study contribute directly to the United Nations Sustainable Development Goal 4 (SDG 4: Quality Education) by supporting inclusive and equitable education through early detection of school disengagement and the promotion of timely, targeted interventions. By enabling counsellors to identify at-risk students more efficiently, the system supports efforts to reduce dropout rates and improve student retention and well-being. Additionally, the use of digital decision-support tools aligns with SDG 9 (Industry, Innovation, and Infrastructure) by leveraging innovative technology to strengthen educational support systems.

Despite these contributions, several limitations should be acknowledged. The model's moderate accuracy and reliance on a relatively limited dataset constrain its generalizability and predictive precision. Additionally, the evaluation of usability and acceptance captures initial perceptions rather than long-term adoption behaviour, which may differ over time. These limitations highlight the need for future research involving larger, more diverse populations, longitudinal validation, and continued model refinement.

In conclusion, integrating technical evaluation with usability and acceptance assessments provides a holistic understanding of the system's strengths and limitations. While further refinement of the predictive model, such as incorporating larger, more diverse datasets, is necessary to enhance accuracy, the findings demonstrate the promise of MyBuddy as a scalable and impactful tool to support sustainable, technology-enabled educational interventions. Future research should focus on broader validation across diverse educational settings to strengthen its contribution to sustainable development and evidence-based educational policy.

ACKNOWLEDGEMENT

This research is funded by Yayasan Sime Darby (YSD) and Kedah State Government through the Industrial Research Grant Scheme (SO Code 21039 and 14989). The authors fully acknowledge YSD and the Kedah State Government for their approval of funding, which made this important research viable and effective. We highly appreciate and acknowledge the cooperation and contributions of the Kedah State Education Department, which participated and assisted in this study.

REFERENCES

Alturki, S., & Alturki, N. (2021). Using educational data mining to predict students' academic performance for applying early interventions. *Journal of Information Technology Education: Innovations in Practice*, *20*, 121–137. https://doi.org/10.28945/4835

Anderson, R. C., Graham, M., Kennedy, P., Nelson, N., Stoolmiller, M., Baker, S. K., & Fien, H. (2019). Student agency at the crux: Mitigating disengagement in middle and high school. *Contemporary Educational Psychology*, *56*, 205–217. https://doi.org/10.1016/j.cedpsych.2018.12.005

Aulck, L., Nambi, N., Velagapudi, N., Blumenstock, J. E., & West, J. D. (2019). Mining university registrar records to predict first-year undergraduate attrition. *Proceedings of the 12th International Conference on Educational Data Mining* (pp. 150–159).

Aziz, M. N. A., Bukhari, N., Yusoff, N. M., Ibrahim, Y., Karim, A. M. A., Awang, M. I., & Shapii, A. (2023). A study on the implementation of remote learning: Malaysian students' struggles and suggestions for improvement. *International Journal of Evaluation and Research in Education*, *12*(1), 311-318. https://doi.org/10.11591/ijere.v12i1.23590

Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). Methodologies for data quality assessment and improvement. *ACM Computing Surveys*, *41*(3), Article 16. https://doi.org/10.1145/1541880.1541883

Bjugstad, A., Cardoso, J. B., Chen, T. A., Brabeck, K. M., & Borja, S. (2023). Exploring social and environmental predictors of school engagement among first- and second-generation Latino youth: A multidimensional approach. *Psychology in the Schools*, *61*(4), 1375–1392. https://doi.org/10.1002/pits.23119

Cannistrà, M., Masci, C., Ieva, F., Agasisti, T., & Paganoni, A. M. (2022). Early-predicting dropout of university students: an application of innovative multilevel machine learning and statistical techniques. *Studies in Higher Education*, *47*(9), 1935–1956. https://doi.org/10.1080/03075079.2021.2018415

Cocea, M., & Weibelzahl, S. (2006). Can log files analysis estimate learners' level of motivation? *Proceeding of Lernen – Wissensentdeckung – Adaptivität* (pp. 32–35). Universität Hildesheim National College of Ireland Repository. https://nbn-resolving.org/urn:nbn:de:gbv:hil2-opus-722

Cristea, A. I., Alamri, A., Alshehri, M., Pereira, F. D., Toda, A. M., De Oliveira, E. H. T., & Stewart, C. (2024). The engage taxonomy: SDT-based measurable engagement indicators for MOOCs and their evaluation. *User Modeling and User-Adapted Interaction*, *34*(2), 323–374. https://doi.org/10.1007/s11257-023-09374-x

Delen, D. (2011). Predicting student attrition with data mining methods. *Journal of College Student Retention: Research, Theory and Practice*, *13*(1), 17–35. https://doi.org/10.2190/CS.13.1.b

Elbadrawy, A., Polyzou, A., Ren, Z., Sweeney, M., Karypis, G., & Rangwala, H. (2016). Predicting student performance using personalized analytics. *Computer*, *49*(4), 61–69. https://doi.org/10.1109/mc.2016.119

Helal, S., Li, J., Liu, L., Ebrahimie, E., Dawson, S., Murray, D. J., & Long, Q. (2018). Predicting academic performance by considering student heterogeneity. *Knowledge-Based Systems*, *161*, 134–146. https://doi.org/10.1016/j.knosys.2018.07.042

Henry, K. L., Knight, K. E., & Thornberry, T. P. (2011). School disengagement as a predictor of dropout, delinquency, and problem substance use during adolescence and early adulthood. *Journal of Youth and Adolescence*, *41*(2), 156–166. https://doi.org/10.1007/s10964-011-9665-3

Hung, J., Shelton, B. E., Yang, J., & Du, X. (2019). Improving predictive modeling for at-risk student identification: A multistage approach. *IEEE Transactions on Learning Technologies*, *12*(2), 148–157. https://doi.org/10.1109/tlt.2019.2911072

Järvinen, T., & Tikkanen, J. (2019). Student disengagement in comprehensive school in Turku, southwest Finland. In J. Demanet, & M. Van Houtte (Eds.), *Resisting education: A cross-national study on systems and school effects* (pp. 81–102). Springer. https://doi.org/10.1007/978-3-030-04227-1_4

Johnson, E., & Semmelroth, C. (2010). The predictive validity of the early warning system tool. *NASSP Bulletin*, *94*(2), 120–134. https://doi.org/10.1177/0192636510380789

Katsantonis, I., Gibbons, R. A., Symonds, J. E., & Costello, N. (2024). To persist or not? Examining the relations between parental education, self-regulation, school engagement and persistence in post-compulsory education. *British Educational Research Journal*, *50*(4), 2020–2042. https://doi.org/10.1002/berj.4012

Kiefer, S. M., Ellerbrock, C., & Alley, K. (2014). The role of responsive teacher practices in supporting academic motivation at the middle level. *RMLE Online*, *38*(1), 1–16. https://doi.org/10.1080/19404476.2014.11462114

Korkmaz, Ö., & Aydın, M. N. (2025). Detection of early school drop out in vocational and technical high schools in Turkey. *Sage Open*, *15*(3). https://doi.org/10.1177/21582440251370443

Kulkarni, R., Choudhari, G., Bhavik, M., Bura, R., & Bhosale, V. (2025). Gamifying early math education: An innovative AI game for children. *Journal of Information Technology Education Innovations in Practice*, *24*, 014. https://doi.org/10.28945/5595

Martins, J., Cunha, J., Lopes, S., Moreira, T., & Rosário, P. (2021). School engagement in elementary school: A systematic review of 35 years of research. *Educational Psychology Review*, *34*(2), 793–849. https://doi.org/10.1007/s10648-021-09642-5

Mason, C., Twomey, J., Wright, D., & Whitman, L. (2017). Predicting engineering student attrition risk using a probabilistic neural network and comparing results with a backpropagation neural network and logistic regression. *Research in Higher Education*, *59*(3), 382–400. https://doi.org/10.1007/s11162-017-9473-z

McFarland, J. L. (2023). *Teachers' perceptions on effective strategies to retain Black ninth-grade students* [Doctoral dissertation, Arkansas State University]. https://arch.astate.edu/all-etd/155

Miguéis, V., Freitas, A., Garcia, P. J., & Silva, A. (2018). Early segmentation of students according to their academic performance: A predictive modelling approach. *Decision Support Systems*, *115*, 36–51. https://doi.org/10.1016/j.dss.2018.09.001

Mikkay, E. L. W., Jalil, N. A., Salleh, N. M., & Idris, I. (2023). Dropout early warning system (DEWS) in Malaysia's primary and secondary education: A conceptual paper. In M. Al-Emran, M. A. Al-Sharafi & K. Shaalan (Eds.), *International Conference on Information Systems and Intelligent Applications* (pp. 427-434). Springer. https://doi.org/10.1007/978-3-031-16865-9_33

Mishra, N., & Silakari, S. (2012). Predictive analytics: A survey, trends, applications, opportunities & challenges. *International Journal of Computer Science and Information Technologies*, *3*(3), 4434-4438.

Monk, E. F., Cantor, W., Antonucci, Y. L., & Park, E. E. (2025). Immersing students: The impact of virtual reality on student engagement and team dynamics in a business simulation. *Journal of Information Technology Education Innovations in Practice*, *24*, Article 17. https://doi.org/10.28945/5608

Murphy-Graham, E., Cohen, A. K., & Pacheco-Montoya, D. (2020). School dropout, child marriage, and early pregnancy among adolescent girls in rural Honduras. *Comparative Education Review*, *64*(4), 703–724. https://doi.org/10.1086/710766

Nagy, M., & Molontay, R. (2018). Predicting dropout in higher education based on secondary school performance. *Proceedings of the IEEE 22nd International Conference on Intelligent Engineering Systems*, *Las Palmas de Gran Canaria, Spain,* 389–394. https://doi.org/10.1109/INES.2018.8523888

Nam, S., Frishkoff, G., & Collins-Thompson, K. (2017). Predicting students disengaged behaviors in an online meaning-generation task. *IEEE Transactions on Learning Technologies*, *11*(3), 362–375. https://doi.org/10.1109/tlt.2017.2720738

Neild, R. C. (2009). Falling off track during the transition to high school: What we know and what can be done. *The Future of Children*, *19*(1), 53–76. https://doi.org/10.1353/foc.0.0020

Nielsen, J. (1993). *Usability engineering*. Morgan Kaufmann. https://doi.org/10.1016/B978-0-08-052029-2.50009-7

Roslan, N., Jamil, J. M., Shaharanee, I. N. M., & Alawi, S. J. S. (2024). Prediction of student dropout in Malaysian's Private Higher Education Institute using data mining application. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *45*(2), 168–176. https://doi.org/10.37934/araset.45.2.168176

Sani, N. S., Fikri, A., Ali, Z., Zakree, M., & Nadiyah, K. (2020). Drop-out prediction in higher education among B40 students. *International Journal of Advanced Computer Science and Applications*, *11*(11). https://doi.org/10.14569/ijacsa.2020.0111169

Segura, M., Mello, J., & Hernández, A. (2022). Machine Learning prediction of university student dropout: Does preference play a key role? *Mathematics*, *10*(18), 3359. https://doi.org/10.3390/math10183359

Sharma, D. (2026). Climate change, migration, and school disengagement in a globalised world: governance challenges, educational inequality, and the role of AI and traditional knowledge. *International Journal of Social Sciences Language and Linguistics*, *6*(1), 34–43. https://doi.org/10.55640/ijssll-06-01-05

Skenderidou, I., Leontopoulos, S., Stafylis, N., & Skenderidis, P. (2025). School dropout: causes, consequences, and strategies for prevention. *European Journal of Education Studies*, *12*(11), 176–196. https://doi.org/10.46827/ejes.v12i11.6279

Soland, J., Jensen, N., Keys, T. D., Bi, S. Z., & Wolk, E. (2019). Are test and academic disengagement related? Implications for measurement and practice. *Educational Assessment*, *24*(2), 119–134. https://doi.org/10.1080/10627197.2019.1575723

Subramainan, L., Mahmoud, M. A., Ahmad, M. S., & Yusoff, M. Z. M. (2016). Evaluating students engagement in classrooms using agent-based social simulation. *Proceedings of the 2nd International Symposium on Agent, Multi-Agent Systems and Robotics, Bangi, Malaysia,* 34–39. https://doi.org/10.1109/ISAMSR.2016.7809999

Sumardi, N. A., Halif, M. M., Hassan, N., & Dzulkalnine, N. (2023). EDIUSY: The solution of student disengagement. *International Teaching Aid Competition* (pp. 135–141). Universiti Teknologi MARA Cawangan Kedah. https://ir.uitm.edu.my/id/eprint/83300/1/83300.pdf

Szabó, L., Zsolnai, A., & Fehérvári, A. (2024). The relationship between student engagement and dropout risk in early adolescence. *International Journal of Educational Research Open*, *6*, 100328. https://doi.org/10.1016/j.ijedro.2024.100328

Trinidad, J. E. (2023). *Organizational networks and school improvement: The spread of early warning indicators in a decentralized educational system* [Doctoral dissertation, The University of Chicago].

Vázquez-Nava, F., Vázquez-Rodríguez, E. M., Vázquez-Rodríguez, C. F., & Betancourt, N. V. O. (2019). High school dropout: Association with family structure, maternal employment, and health-risk habits among female Mexican adolescents. *Journal of Child and Family Studies*, *28*(12), 3307–3314. https://doi.org/10.1007/s10826-019-01505-6

Xu, E. Y., MacSweeney, N., Thng, G., Barbu, M. C., Shen, X., Kwong, A. S. F., Romaniuk, L., McIntosh, A., Lawrie, S. M., & Whalley, H. C. (2024). Assessing a prediction model for depression risk using an early adolescent sample with self-reported depression. *JCPP Advances*, *5*(2), e12276. https://doi.org/10.1002/jcv2.12276

AUTHORS

Laura Lim Sie-Yi is a doctoral candidate in Information Technology at Universiti Utara Malaysia, whose academic and professional endeavours are grounded in the application of technology to address societal challenges. Her scholarly interests lie in data analytics and game-based research, with a particular emphasis on enhancing learning engagement among older adults through inclusive, innovative technological interventions. She possesses practical experience in data-driven research and analytical methodologies, which informs her approach to designing and implementing impactful studies. In addition to her individual research pursuits, she demonstrates a strong commitment to community-oriented initiatives, actively seeking opportunities that contribute to social well-being and educational development. Her current doctoral research focuses on developing a cognitive model to identify, understand, and mitigate factors associated with student dropout, thereby supporting more effective and equitable educational outcomes.

Noraziah ChePa is an Associate Professor at the School of Computing, Universiti Utara Malaysia (UUM), where she has served since May 2000. With over two decades of academic experience, she has taught more than 30 courses in information technology at both the undergraduate and postgraduate levels and supervised numerous postgraduate students. Her research interests focus on neuro-modelling, particularly in health-related domains, with a strong emphasis on gerontology. She is an active researcher, having led more than 30 research projects and produced 35 intellectual properties as a Principal Inventor. She has also published over 60 scholarly works in reputable journals and conferences. In recognition of her contributions to research and innovation, she has received more than 80 awards at national and international levels. Her current research spans neuro-modelling, game-based modelling, and technology-driven solutions for health and ageing, reflecting her commitment to advancing impactful, innovative research.