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AI vs Human Judgement: A Comparative Analysis of MyBuddy Application and Manual Assessment in Predicting At-Risk Students

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13.1 Introduction

School dropout is often linked to disengagement, which can stem from various factors such as academic difficulties, behavioural issues, and personal hardships (Szabó et al., 2024; Washor & Mojkowski, 2014). Some students, while remaining enrolled, may still experience disengagement, which can eventually lead to their withdrawal from school. As a result, their future is put at risk, highlighting not only inadequate preparation for postsecondary education but also the broader negative consequences that follow (Bóbbó et al., 2022; Marlow & Rehman, 2021; Robison et al., 2017; Sagatun et al., 2014). Previous studies have explored various methods and models to detect student disengagement and school dropout (Fredricks et al., 2019; Garrett-Peters et al., 2019; Järvinen & Tikkanen, 2019; Soland et al., 2019; Sumardi et al., 2023). However, these approaches often lack comprehensiveness due to the complex and multifaceted nature of student disengagement, which is influenced by a wide range of factors (Bills & Howard, 2021).

The complexity of school disengagement, driven by multiple interrelated factors, has made it challenging to develop a robust computational model for early prediction. To address this gap, this study introduces a heterogeneous adaptive computational model designed to identify students at risk of dropping out. This model has been integrated into the *MyBuddy* application and has undergone a comprehensive technical assessment (Chepa et al., 2023). However, its effectiveness depends on the precise calibration of key parameters to ensure that its predictions align with real-world data. The model's

intervention efforts. These differences highlight the potential of smart prediction in identifying at-risk students more effectively, ensuring that those in need receive timely support and intervention.

13.7 Towards Smarter Education: AI and the Future of Student Support

This study highlights the effectiveness of *MyBuddy* in predicting at-risk students compared to traditional manual assessments conducted by school counsellors. The results demonstrate that while human judgement often categorises the majority of students as low risk, *MyBuddy* identifies a higher number of students in the medium- and high-risk categories, ensuring that more students receive timely intervention. A key weakness of manual assessment is the presence of bias, as counsellors' judgements are influenced by personal perceptions, past experiences, and subjective interpretations of students' behaviour. In contrast, *MyBuddy* applies a standardised, data-driven approach that eliminates bias, offering a more objective and consistent risk classification.

By integrating intelligent prediction models, *MyBuddy* enhances the accuracy of early detection efforts, paving the way for proactive intervention strategies. This study underscores the potential of AI-driven tools in complementing and improving traditional assessment methods in educational settings. Future research could explore refining *MyBuddy*'s predictive capabilities by utilising larger datasets and real-time monitoring to further enhance its impact. Ultimately, leveraging smart prediction systems can significantly improve student support mechanisms, ensuring that no at-risk student is overlooked due to human bias. This study plays an important role in promoting inclusive and equitable quality education by facilitating early intervention strategies that enhance student retention and success, aligning with the United Nations' Sustainable Development Goal 4 (Quality Education).

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