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The Relationship between Well-being and Academic Achievement: A Comprehensive Cross-Sectional Analysis of System Wide Data from 2016–2019

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Abstract

Learning analytics research has long flagged the importance of social and emotional well-being on student academic progress and outcomes. However, few studies have examined the interplay between well-being measures and academic outcomes at scale. This research examined the relationship between the Well-being Engagement Collection (WEC) index and student academic outcomes, using cross-sectional panel data from 215,635 students in Years 4–10 in South Australia, spanning 2016 to 2019. Using linear hierarchical mixed models, results indicate a modest impact of the WEC index on these outcomes, with learning readiness emerging as the most influential component. The effects of the WEC index remained stable across various student year levels and census periods. A notable finding was the more pronounced influence of the WEC index on male students, particularly in literacy, suggesting gender-specific variations in the role of emotional well-being on academic achievement. The study underscores the potential of learning analytics in future investigations to deepen our understanding of the nexus between socio-emotional factors and academic outcomes.

Notes for Practice

- Integrating well-being measures like the Well-being Engagement Collection (WEC) index in learning analytics offers insights into its influence on academic outcomes, advocating for a holistic educational approach.
- The WEC index highlights learning readiness as its key factor, emphasizing the importance of student preparedness for boosting academic performance.
- Future research should explore gender-specific strategies, addressing unique socio-emotional needs to improve educational outcomes, especially in literacy for male students.

Keywords
Student well-being, academic achievement, Well-being Engagement Collection

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1. INTRODUCTION

Since the inception of the field of learning analytics (LA), researchers have focused on developing scalable and novel practices to improve student learning outcomes. Most of these works have been dedicated to establishing associations between online user behaviour, trace data, and student academic performance. In so doing, a primary objective for LA has centred on the creation of predictive models (Conijn et al., 2016; Sghir et al., 2023). That is, the provision of actionable information that can accurately identify students at risk of attrition or failure early in their academic studies. Early research in this vein drew heavily on trace data captured from learning management systems (LMSs) associated with future academic performance (Macfadyen & Dawson, 2010). The volume of data from education technologies quickly expanded the opportunities for LA researchers to demonstrate impact through the identification of lead indicators of learning behaviour predictive of academic performance. In so doing, the diverse examples of how LMS- or technology-mediated data are applied in education research effectively decreased the reliance on more time-consuming data-collection methods such as self-report surveys. While the push for trace data has been expedient for our research activities, there remains a gap in our understanding of student emotions, motivation, and overall interests.

Despite the ability to analyze student learning behaviour in almost real time, there remain challenges related to the transferability of predictive models across programs and courses within an institution (Gašević et al., 2016). To date, the translation of predictive models to scaled actionable practice has been poor at best. Dawson et al. (2018) noted the widening gap between LA research outcomes and the translation to scaled practice. The nuanced and individualized nature of student learning and teaching practice has, in effect, impeded the rapid deployment of LA models. While the models are statistically accurate, they fail to account for the various contextual factors and individual differences required for teacher action. Herein lies the core of the problem for personalized learning and feedback practices. Student learning is an inherently complex process. All students bring diverse experiences, understandings, skills, study approaches, and motivations to their learning pursuits (Winne & Hadwin, 1998). The ability to capture trace data related to a student’s online study behaviour lacks the necessary insights into their motivation, goals, and well-being. These socio-emotional dimensions strongly influence student outcomes and the student’s ability to monitor and regulate their learning (Azevedo et al., 2017).

Despite the importance of socio-emotional constructs such as well-being, there remains a gap in the literature concerning how these variables interplay and impact on student academic performance (Amholt et al., 2020; Bücker et al., 2018). The studies undertaken to date are largely constrained to small datasets and snapshots in time. There are very few large-scale studies in this domain. This present study draws on data from the South Australian Well-being and Engagement Collection (WEC) to examine the impact of student well-being and engagement on their academic achievement over several years (Gregory & Brinkman, 2020). The WEC represents a significant advancement in understanding the multifaceted variables that influence academic outcomes in the school sector. The WEC delves into non-academic factors crucial to learning and participation, and assesses emotional well-being, school engagement, and learning readiness. Comparing the magnitude of different well-being measures’ effects on academic outcomes is valuable to policymakers and school systems as it can inform targeted interventions and resource allocation to support both student well-being and academic achievement effectively. Similarly, LA can play a crucial role by identifying gaps in student well-being and academic performance. LA provides data-driven insights that help policymakers and educators pinpoint areas needing intervention, ensuring resources are allocated where they are most needed. This targeted approach not only enhances student support but also promotes a more efficient and effective educational system, ultimately leading to improved overall student outcomes and well-being.

2. LITERATURE REVIEW

2.1. Capturing Socio-emotional Data

In recent years, the K–12 educational landscape has undergone a transformation, moving away from a traditional emphasis on academic knowledge and towards fostering competencies and socio-emotional skills (Milligan, 2020). Socio-emotional learning often refers to attempts to “*explain the scope of learning outside traditional cognitive lenses*” (Joksimović et al., 2020, p. 1). While this shift gains momentum, the challenge of assessing these competencies, particularly socio-emotional skills, remains a critical concern since these constructs are intricate and multifaceted and can be difficult to measure (Joksimović et al., 2020). Consequently, researchers, educators, and policymakers have been advocating for a paradigm shift in assessment methods away from the cognitive domain’s traditional metrics (Barthakur et al., 2023). This shift is driven by the intersection of digitalization and advancements in contemporary education research, which pave the way for interdisciplinary approaches to assess student social and emotional skills. By analyzing patterns in student interactions, behaviours, and even biometric data, LA can provide a more holistic view of student well-being and engagement (Gašević et al., 2015). This integration is essential for developing a comprehensive understanding of student development and for creating learning environments that support both academic and socio-emotional growth (Ifenthaler & Yau, 2020). However, the integration of socio-emotional indicators, such as student emotional states during learning activities, is still limited and is often focused primarily on identifying students at risk of poor performance (Arnold & Pistilli, 2012). This gap highlights the need for more comprehensive research and development in the field of LA to fully leverage its potential in assessing and supporting socio-emotional skills. While some progress has been made, the current use of LA and educational data mining (EDM) often falls short in providing the necessary insights into socio-emotional development (Ifenthaler & Yau, 2020; Joksimović et al., 2020).

To comprehensively capture these non-academic factors, it becomes imperative to implement large-scale surveys at the systems level. Numerous studies underscore the pivotal role played by socio-emotional factors in shaping student achievement, workplace readiness, and overall well-being (Amholt et al., 2020; Bücker et al., 2018; Miller et al., 2013). Research shows that non-academic attributes significantly influence academic performance, physical health, substance dependence, personal finances, and criminal offending in adulthood (Cadime et al., 2016; Mendez, 2015; Moffitt et al., 2011). Consequently, education policymakers worldwide acknowledge the importance of fostering social and emotional development within their education system. However, the measurement of these skills still receives insufficient attention compared to academic achievement (Sellar, 2015). In many countries, the primary data collected on school students remains limited to standardized academic tests, leading to an overemphasis on academic achievement in educational discourse (Gregory et al., 2019). To shift this focus and promote holistic student development, it is imperative to collect comprehensive data on student well-being using consistent tools. This approach, as exemplified by South Australia's Well-being and Engagement Collection (WEC), allows educators, schools, communities, and education systems to monitor student progress and assess the effectiveness of policies and programs aimed at enhancing student well-being (Gregory et al., 2019, 2021).

2.2. Emotional Well-being

Student well-being is a multidimensional concept, and its definitions vary across the research literature. In this study, emotional well-being is operationalized through measures of subjective well-being (e.g., life satisfaction and happiness), through positive traits and character strengths (e.g., optimism), and the absence of psychological distress (e.g., sadness and worries; Gregory et al., 2021; Kern et al., 2015; Seligman & Csikszentmihalyi, 2000). Life satisfaction, a holistic assessment of one's quality of life, has been positively correlated with academic performance (Antaramian, 2017; Diseth & Samdal, 2014). Research suggests that students with heightened life satisfaction often benefit from a conducive learning environment, characterized by motivation, engagement, and a profound sense of belonging, all quintessential for academic success (Lyons & Huebner, 2016). Concurrently, optimism, defined as the general expectation of positive outcomes, plays a salient role in academic outcomes (Gómez Molinero et al., 2018). Students with an optimistic disposition exhibit resilience, viewing academic challenges as surmountable, leading to efficacious coping strategies, diminished stress levels, and enhanced academic performance (Gómez Molinero et al., 2018). In contrast, sadness, anxiety, and depression can directly and indirectly impede academic achievement (Liu et al., 2018; Vilaplana-Pérez et al., 2021). Such emotional states can attenuate motivation, cognitive function, and attention, all integral for effective learning (Liu et al., 2018; Vilaplana-Pérez et al., 2021). Persistent sadness can also be a precursor to severe mental health issues, further exacerbating academic challenges (Khesht-Masjedi et al., 2019). Similarly, chronic worry, a pervasive concern in the academic realm, can be detrimental (de Lijster et al., 2018). Students overwhelmed by incessant worries often grapple with concentration challenges, leading to compromised information retention and comprehension. Such chronic worry can culminate in anxiety disorders, further intensifying academic impediments (de Lijster et al., 2018). However, while the relationship between emotional well-being and academic performance is well-documented, there is a significant gap in LA research concerning the integration and analysis of emotional well-being data. Current LA systems predominantly focus on academic metrics and behavioural data, with limited incorporation of socio-emotional indicators such as life satisfaction, optimism, and psychological distress (Joksimović et al., 2020).

2.3. Engagement with School

Considering the holistic development of students, their engagement with school emerges as a crucial component of the educational experience, reflecting the degree to which students actively participate in and dedicate themselves to their learning (Tomaszewski et al., 2020; Upadyaya & Salmela-Aro, 2013). It goes beyond mere attendance, involves a deep connection to the adults at school and at home, positive interactions with teachers and peers, and depends on a positive school climate (Tomaszewski et al., 2020; Upadyaya & Salmela-Aro, 2013). Student engagement plays a pivotal role in shaping academic success, personal development, and overall well-being (Boulton et al., 2019).

The level of student engagement within classrooms is intrinsically linked to their relational connectedness with the adults present within the school and the prevailing climate of the institution (Quin et al., 2018; van Rooij et al., 2017). Enhanced relationships between educators and students, underpinned by efficacious communication strategies, have the potential to cultivate an optimal learning atmosphere, thereby amplifying student engagement (Kraft & Dougherty, 2013; Tarabini et al., 2019). Concurrently, an affirming school climate, delineated by mutual respect and an inherent sense of communal belonging, can increase levels of student engagement. In contrast, adverse perceptions of the school environment — particularly those emanating from instances of peer-induced bullying — can precipitate diminished student engagement (Mahdiuon et al., 2020; Yang et al., 2018).

Similarly, a sense of belonging within the school and among peers plays an important role in student engagement (Korpershoek et al., 2020; Wentzel, 2022). When students feel that their school promotes active participation and involvement, they are more likely to be engaged (Korpershoek et al., 2020; Wentzel, 2022). Research shows that intimate friendships can serve as a support system for students, enhancing their engagement with school (Hakimzadeh et al., 2016; Moses & Villodas, 2017). Such relationships provide emotional and academic support, fostering a conducive learning environment (Juvonen et al., 2012). Bullying and victimization can have profound negative effects on student engagement. Students who experience bullying, whether as victims or perpetrators, often report lower levels of school engagement (Yang et al., 2018).

LA research has extensively studied student engagement using digital trace data collected through education platforms such as LMSs. However, engagement with learning is not solely influenced by in-school factors. Connectedness to adults at home and in the community can also play a significant role (Ahmadi et al., 2020). For instance, parental engagement in student learning has been shown to make a considerable difference in student achievement (Harris & Goodall, 2008). Authors have also shown that supportive parents who communicate about academic expectations, and actively participate in their middle school child's education significantly improved various school-related outcomes, including grades and behaviour (Woolley & Grogan-Kaylor, 2006). This work was expanded to demonstrate that students who had supportive adults in their lives, including at home, at school, and in the community, showed higher levels of emotional and behavioural involvement in school (Woolley & Bowen, 2007). To develop a more comprehensive picture of student engagement, LA research should move beyond trace data and explore other measures to gain a more comprehensive understanding of student engagement.

2.4. Learning Readiness

Learning readiness, grounded in the theory of self-regulated learning (SRL), encompasses several key components. SRL has been broadly defined as the ability to regulate cognition, behaviours, and emotions to achieve academic goals (Pandey et al., 2018; Korucu et al., 2022). However, similar constructs have been defined differently across various disciplines, including developmental psychology and personality (McClelland et al., 2014). Generally, SRL is operationalized as the skills needed to moderate behaviour in an academic context, such as managing time, attention, goal planning, and delayed gratification (Rodríguez et al., 2022).

Previous versions of the WEC have operationalized elements of SRL through the construct of learning readiness. One of these elements is the academic self-concept, which refers to student perceptions of their own academic abilities (Morinaj & Hascher, 2022). A positive academic self-concept can boost confidence and motivation, leading to better learning outcomes (Khalaila, 2015; Parker et al., 2014). Research findings indicate that students with a positive academic self-concept are more likely to engage in challenging tasks, persist in the face of difficulties, and achieve higher academic performance (Marsh & Martin, 2011; Wu et al., 2021).

Perseverance is another component of learning readiness and is tied to SRL skills (Kern et al., 2016). Perseverance refers to having the tenacity to stay on task and pursue a goal, despite the challenges that may occur. Kern and colleagues succinctly framed this as finishing things that you start, even if it takes a while (Kern et al., 2016). Students equipped with the knowledge of how to learn, coupled with sustained motivation and emotion management, tend to persevere and persist through challenges (Burleson, 2013; Star, 2015). Studies have shown that perseverance is associated with higher levels of academic achievement and can predict long-term success (Credé et al., 2017). Lastly, flow is a psychological state characterized by a deep and immersive involvement in an activity to the extent that the individual loses track of time, becomes completely absorbed in the task, forgets about everything else, and may even lose awareness of the passage of time. This state is associated with intense focus and enjoyment during the activity (Csikszentmihalyi, 1999). Flow is important because it enhances the learning experience, promotes intrinsic motivation, ensures an optimal challenge level, and contributes to efficient and effective learning (Gregory & Brinkman, 2020). Research has demonstrated that students who frequently experience flow are more engaged and perform better academically (Nakamura & Csikszentmihalyi, 2009; Shernoff et al., 2003). The ability to achieve flow is linked to the development of SRL skills, as students who can effectively manage their learning environment are more likely to enter and sustain this state (Schunk & Zimmerman, 2008).

The components integral to learning readiness — including academic self-concept, perseverance, and the attainment of a state of flow — are rooted in the domain of the learning sciences (Csikszentmihalyi, 1999; Darling-Hammond et al., 2020). These elements collectively shape student regulation efforts towards their learning goals, influencing how they engage with their studies and overall learning experience (Schumacher & Ifenthaler, 2018; Schunk & Zimmerman, 2008). The full impact of these individual constructs in informing pedagogical practices and optimizing learning environments is intricately tied to the growing collaboration between the learning sciences and LA. LA plays a crucial role in this context by providing data-driven insights that enable educators to tailor feedback and interventions to individual student needs. This shift from generic to personalized feedback enhances student engagement and academic performance by addressing specific areas of difficulty and promoting effective learning strategies (Sharif & Atif, 2024). For instance, LA can track student engagement metrics, such as time spent on tasks and participation in online activities, offering a detailed picture of each student's learning process and identifying potential barriers to success (Long & Siemens, 2011). However, the integration of LA with established learning theories remains in its nascent stages, representing a promising yet underexplored frontier in education research and practice (Marzouk et al., 2016; Schumacher & Ifenthaler, 2018).

2.5. Importance for Schooling

If schools focus on measuring and teaching multifaceted well-being, they can empower students to lead flourishing lives, subsequently influencing academic performance (Adler, 2017). This perspective suggests a shift towards an educational paradigm that values both well-being and academic achievement as integral components of a holistic education. Moreover, Adler's perspective highlights a reciprocal relationship between well-being and academic performance (Adler, 2017). When students are mentally and emotionally healthy, they are more likely to be engaged and motivated and perform better academically (Adler, 2017). This suggests that well-being is not just a desirable outcome but also a catalyst for academic success. However, the relationship between well-being and academic achievement is complex. Low-achieving students do not necessarily report low well-being, and high-achieving students do not automatically experience high levels of well-being (Bücker et al., 2018). Such findings emphasize the importance of a nuanced understanding of both well-being and academic achievement. Schools and educators must recognize that while there is a relationship between the two, it is not linear. This understanding can prevent the pitfalls of making assumptions about a student's well-being based solely on their academic performance and vice versa.

It is clear that the mere presence of positive emotions is not sufficient for academic success (Mega et al., 2014). Instead, these emotions foster academic achievement when mediated by SRL (Mega et al., 2014). This underscores the importance of fostering a positive emotional environment for students and equipping them with the skills and motivation to harness these emotions effectively for academic pursuits (Mega et al., 2014; Williams et al., 2013). Similarly, DiPerna et al. (2005) show a positive association between academic achievement and study skills, further emphasizing the role of engagement. Interestingly, both these factors are predicted by motivation and interpersonal skills. This interconnectedness suggests that while academic skills are crucial, the role of interpersonal skills and motivation cannot be sidelined. It emphasizes a holistic approach to education, where students are trained academically *and* nurtured emotionally and socially.

Conflicting studies on the relationship between well-being and academic achievement can be found in the research literature (Amholt et al., 2020). However, there is a dearth of LA research investigating the various facets of well-being, socio-emotional factors, and academic achievement. LA allows the collection of fine-grained student data that holds the potential to understand the link between well-being and academic achievement. LA also provides a promising avenue for conducting longitudinal studies to uncover the developmental trajectory of these various facets over time.

2.6. Gender Differences

Research highlights inconsistencies in gender differences across multiple facets of learning. For example, when it comes to academic self-concept, studies reveal gender-based patterns. Some studies indicate that boys have a stronger self-concept in mathematics than girls (Girelli, 2023; Mejía-Rodríguez et al., 2021). Perseverance, linked to SRL skills, has also shown gender-related differences, with females often doing better than males in online SRL, especially during challenging periods like the COVID-19 lockdown (X. Liu et al., 2021). Pekrun's Control Value Theory (2006) underscores the significance of emotions in academic achievement, positing that these emotions are shaped by one's beliefs about control and the value of achievement tasks (Lazarides & Raufelder, 2021). When viewed through a gendered lens, this theory offers insights into how societal norms and cultural values might influence gender disparities in academic outcomes (Eriksson et al., 2020). Eriksson et al. (2020) argue that gender egalitarian values can influence these control and value perceptions, suggesting that in more gender-egalitarian societies, students of all genders may experience more similar academic achievement emotions. This suggests that societal values can moderate the impact of control and value perceptions on academic emotions. Furthermore, the broader societal milieu, including pressures to conform to gender norms, can subtly influence learning-related aspects like academic self-efficacy (Vantieghem & Van Houtte, 2015).

Emotional well-being is crucial for optimal learning and academic achievement, and studies have highlighted gender differences among students. For example, females often report higher levels of emotional expressiveness than males (Deng et al., 2016). These differences in emotional well-being can have significant implications for learning, as students who feel emotionally supported and understood are more likely to engage actively in the learning process (Renshaw et al., 2015). Furthermore, gender differences in subjective well-being have been noted, with a notable gender gap emerging around the age of 12 (Esteban-Gonzalo et al., 2020). School engagement, too, has gendered nuances. Research indicates that females often engage more than males academically, fostering positive relationships with peers and educators (Bang et al., 2020). Gender also influences learning readiness. McGeown et al. (2012) suggest that females might be more intrinsically motivated than males during early literacy education. In a 2013 meta-analysis, Huang (2013) found that males have slightly higher self-efficacy than females in mathematics, computer science, and social sciences. Conversely, females have a slightly higher self-efficacy for language and arts (Huang, 2013). In summary, there are gender differences in various learning facets, from emotional well-being to school engagement. Recognizing and addressing these disparities can guide educators towards a more inclusive and balanced educational landscape.

2.7. The Present Study

In this present study, we aimed to investigate the relationship between the various measures of well-being and academic outcomes. As far as we are aware, this study represents results from the largest sample globally of administratively linked data across well-being and academic outcomes, including more than 200,000 students. The data spans late primary and all grades in high school through an annual rolling population monitoring system. Specifically, this study aimed to determine the associations between profiles of students using self-reported measures of well-being. Our research questions are as follows:

1. What are the associations between student self-reported measures of well-being (e.g., sadness, worries, life satisfaction, optimism, happiness, perseverance, flow) and their academic outcomes in reading, spelling, grammar, writing, and numeracy?
2. How do school-related factors (e.g., school engagement, connectedness to adults at school, school climate, school belonging) influence student academic performance in reading, spelling, grammar, writing, and numeracy?
3. What is the relationship between peer-related factors (e.g., peer belonging, friendship intimacy, bullying/victimization) and student academic outcomes in reading, spelling, grammar, writing, and numeracy?
4. How does student emotional and cognitive engagement with teachers correlate with their academic achievements in reading, spelling, grammar, writing, and numeracy?

In all analyses, we consider gender and socioeconomic factors, recognizing their known impact on both student well-being and academic performance. Although simply reporting cross-sectional associations between these measures, the large sample size allows for confidence in the results, even after controlling for confounding factors, and also includes interaction terms on the models. Although we recognize that in any modern education system, both well-being and academic outcomes are important in and of their own right, it is still of interest to determine the magnitude of the relationship between them.

3. METHODS

3.1. Data Source and Study Design

The project used time series cross-sectional data from 2016 to 2019 from the South Australian Well-being and Engagement Collection (WEC), which can be accessed publicly at an aggregate level (Lam et al., 2023) or on request at the unit level (Gregory et al., 2021). The WEC is an annual survey conducted by the South Australian Department for Education (DfE) during term 1, typically in March, with all schools in South Australia’s public education system invited to participate. Data linkage of WEC to student census and academic outcomes (NAPLAN, PAT-R, and PAT-M; see section 3.3.4) was facilitated by the DfE, which supplied anonymized data to ensure participant privacy and confidentiality. WEC participants comprise students in years 4 to 12 from the public South Australian school system. In the lifetime of the WEC (2016–current), there have been over 900,000 observations in total. The survey was predominantly administered through online platforms, although a subset of schools opted for a paper-based format. A parental opt-out consent procedure was implemented to maximize participation rates and ensure the representativeness of the collected data.

3.2. Participants

Due to data limitations, only data from 2016–2019 could be successfully linked for analysis. Still, over 600,000 valid WEC responses were collected over this period, with 322,192 observations having successful linkage to census demographic information. Limiting the sample to years 4–10 leaves the final sample with 215,635 students. The sample is further reduced as the academic outcomes of focus (NAPLAN, PAT-R, and PAT-M) are not administered across the entire year level. NAPLAN is completed in Years 3, 5, 7, and 9, with only Year 5, 7, and 9 within the WEC cohort, resulting in a reduced sample of approximately 90,000 for NAPLAN outcomes. PAT is administered from Years 4–10, resulting in the full 215,635 sample being used. A diagram of the linkage flowchart is available in the appendix.

3.3. Measures

The WEC survey consists of four constructs: 1) emotional well-being, 2) engagement with school, 3) learning readiness, and 4) health and well-being (for more information on these constructs, see Gregory et al., 2019). Each of these constructs can be broken down into separate scales formed from approximately 230 individual questions. For this analysis, we focused on the related constructs of emotional well-being, engagement with school, and learning readiness and their associated scales. All predictors and outcomes of focus were standardized to allow comparison of effect sizes and easier interpretation. Measures were visually assessed for normality, which was found to be adequate and did not require any variable transformation. Four indexes were created using participant WEC data based on the three constructs measured by the WEC, and a fourth index covering all constructs combined.

3.3.1 Emotional Well-being Index

The emotional well-being index was created as the average scale scores of Life Satisfaction, Optimism, Sadness, Worries, Happiness, and Emotion Regulation. Sadness and Worries were reverse coded for the calculation of the index. Psychological Distress (K6) and Resilience were not included since these were only asked in senior years (Years 10–12) and would not align with the available academic outcomes.

3.3.2 Engagement with School

The engagement with school index was created as the average scale scores of Connectedness to adults at school, School climate, School belonging, Peer belonging, Friendship intimacy, Bullying/victimization (physical, verbal, social, and cyber), Emotional engagement with teachers, and Cognitive engagement. All bullying items were reverse coded for the calculation of the index.

3.3.3 Learning Readiness

The learning readiness index was created as the average scale scores of Academic self-concept, Perseverance, and Engagement (flow). Academic self-efficacy, Perfectionistic striving, Perfectionistic concerns, Hope–agency, Hope–pathways, Feelings about the future, and Feelings about after school/work were not included since these were only asked in senior years (Years 10–12) and would not align with academic outcomes.

3.3.4 Outcome Measures (NAPLAN, PAT)

Standardized scores of the National Assessment Program – Literacy and Numeracy (NAPLAN) and Progressive Achievement Tests (PAT) in Numeracy and Reading were considered as measures of academic outcomes. NAPLAN is a compulsory standardized test completed annually by Year 5, 7, and 9 students, assessing academic performance in numeracy, reading, spelling, grammar, and writing. PAT is assessed in reading (PAT-R) and mathematics (PAT-M) and is compulsory within South Australia from Years 3–10. Scores for all outcomes were transformed into standardized scores for comparative interpretation of effect. Due to data linkage constraints, only academic outcome information from 2016 to 2019 was available for use in this analysis.

3.4 Statistical Analyses

All analyses were conducted in STATA 18/BE. Descriptive statistics (Table 1) were calculated based on the successfully linked participants in Years 3–10. Due to the complex hierarchical structure of the dataset, linear mixed effect models with hierarchical random effects of the student nested within the classroom, nested within the school were specified. Grand mean centring was used to facilitate the interpretation of the fixed effects, as the hierarchical modelling already accounted for the between-group effects. Restricted Maximum Likelihood estimation (REML) was specified, however, the advantages compared to standard Maximum Likelihood methods are likely to be negligible due to the large sample size (Kenward & Roger, 1997). The random effect on the individual student was necessary as several students had repeated measurements at multiple time points. Unadjusted models of all independent variables on dependent variables were first modelled. They were then adjusted for sociodemographic variables chosen a-priori, which included student characteristics of year level, gender, Aboriginal or Torres Strait Islander status, whether the student qualified for financial aid (school card), whether the student came from a non-English speaking background, geographical remoteness, parents' highest formal qualification, the family's socioeconomic status as estimated in SEIFA, and an adjustment for the census year (Australian Bureau of Statistics, 2011).

Results Table 1 shows the characteristics of the sample. As the WEC survey expanded across the system, responses gradually increased yearly. Responses generally decrease on year level, likely due to the extra assistance given by the teacher in younger grades. WEC was not collected in Year 4 until 2017, and in Year 10 not until 2019. Student age had a stable mean of around 11.7 years throughout the collection. Overall, there was a slightly higher proportion of male students in each collection year (51%). Aboriginal and Torres Strait Islander students made up nearly 6% of all responses and have been stable over collection years. Students from non-English speaking backgrounds comprised 25% of the sample and were stable. Multiple measures of socioeconomic status were included, including whether the student qualified for financial aid (school card), and measures of geographical socioeconomics in the form of SEIFA and ARIA (Geographical remoteness; Australian Bureau of Statistics, 2011). Notably, 70% of the sample were students based in major cities, and 27% comprised students from the most disadvantaged socioeconomic areas.

Table 1. Sample Characteristics at Data Collection Years 2016–2019

	Enrolment census year data used in the linkage

	2016	2017	2018	2019	Total
N	35,796 (16.6%)	53,132 (24.6%)	61,379 (28.5%)	65,328 (30.3%)	215,635 (100.0%)
Academic Year level					
4	0 (0.0%)	8,862 (16.7%)	10,961 (17.9%)	10,458 (16.0%)	30,281 (14.0%)
5	0 (0.0%)	8,984 (16.9%)	11,379 (18.5%)	10,719 (16.4%)	31,082 (14.4%)
6	9,676 (27.0%)	10,165 (19.1%)	11,157 (18.2%)	10,740 (16.4%)	41,738 (19.4%)
7	9,746 (27.2%)	9,228 (17.4%)	10,375 (16.9%)	9,385 (14.4%)	38,734 (18.0%)
8	8,399 (23.5%)	8,600 (16.2%)	9,033 (14.7%)	8,872 (13.6%)	34,904 (16.2%)
9	7,975 (22.3%)	7,293 (13.7%)	8,474 (13.8%)	7,843 (12.0%)	31,585 (14.6%)
10	0 (0.0%)	0 (0.0%)	0 (0.0%)	7,311 (11.2%)	7,311 (3.4%)
Student – Age in full years (mean (SD))	12.932 (1.218)	11.644 (1.711)	11.544 (1.731)	11.637 (2.007)	11.827 (1.813)
Student – Gender					
Male	18,259 (51.0%)	27,110 (51.0%)	31,288 (51.0%)	33,124 (50.7%)	109,781 (50.9%)
Female	17,537 (49.0%)	26,022 (49.0%)	30,091 (49.0%)	31,708 (48.5%)	105,358 (48.9%)
Other	0 (0.0%)	0 (0.0%)	0 (0.0%)	496 (0.8%)	496 (0.2%)
Student – Aboriginal and/or Torres Strait Islander					
Non-Indigenous	33,909 (94.7%)	50,208 (94.5%)	57,828 (94.2%)	61,710 (94.5%)	203,655 (94.4%)
Indigenous	1,887 (5.3%)	2,924 (5.5%)	3,551 (5.8%)	3,618 (5.5%)	11,980 (5.6%)
Student – Non-English speaking background					
English only	27,745 (77.5%)	41,352 (77.8%)	47,041 (76.6%)	49,935 (76.4%)	166,073 (77.0%)
Non-English speaking background	8,051 (22.5%)	11,780 (22.2%)	14,338 (23.4%)	15,393 (23.6%)	49,562 (23.0%)
Student – School card					
No	26,529 (74.1%)	39,947 (75.2%)	43,458 (70.8%)	58,710 (89.9%)	168,644 (78.2%)
Yes	9,267 (25.9%)	13,185 (24.8%)	17,921 (29.2%)	6,618 (10.1%)	46,991 (21.8%)
Student – Highest education level of parents/guardians					
Year 9 or equivalent or below	743 (2.1%)	1,070 (2.1%)	1,300 (2.2%)	1,355 (2.1%)	4,468 (2.1%)
Year 10 or equivalent	1,531 (4.4%)	2,182 (4.2%)	2,454 (4.1%)	2,551 (4.0%)	8,718 (4.2%)
Year 11 or equivalent	2,991 (8.6%)	3,888 (7.5%)	4,090 (6.8%)	4,088 (6.4%)	15,057 (7.2%)
Year 12 or equivalent	4,947 (14.2%)	6,767 (13.1%)	7,259 (12.1%)	7,151 (11.3%)	26,124 (12.4%)
Certificate I to IV	9,631 (27.7%)	14,826 (28.6%)	17,358 (29.0%)	18,473 (29.1%)	60,288 (28.7%)
Advanced Diploma or Diploma	5,281 (15.2%)	7,616 (14.7%)	8,617 (14.4%)	9,080 (14.3%)	30,594 (14.6%)
Bachelor’s degree or above	9,704 (27.9%)	15,462 (29.8%)	18,739 (31.3%)	20,802 (32.8%)	64,707 (30.8%)
Student – SEIFA 2016 IRSAD Quintile (STATE)					
Most disadvantaged	9,922 (27.8%)	14,729 (27.9%)	16,657 (27.3%)	17,001 (26.1%)	58,309 (27.2%)
2	5,979 (16.8%)	8,842 (16.7%)	10,112 (16.6%)	10,545 (16.2%)	35,478 (16.5%)
3	5,647 (15.8%)	8,173 (15.5%)	9,732 (15.9%)	10,109 (15.5%)	33,661 (15.7%)
4	7,181 (20.1%)	10,755 (20.3%)	12,320 (20.2%)	13,641 (21.0%)	43,897 (20.4%)
Most advantaged	6,944 (19.5%)	10,377 (19.6%)	12,256 (20.1%)	13,767 (21.2%)	43,344 (20.2%)
Student – Geographical remoteness (ARIA)					
Major Cities of Australia	23,774 (66.6%)	36,582 (69.2%)	42,700 (69.9%)	45,573 (70.0%)	148,629 (69.2%)
Inner Regional Australia	5,328 (14.9%)	7,415 (14.0%)	8,543 (14.0%)	9,381 (14.4%)	30,667 (14.3%)
Outer Regional Australia	5,116 (14.3%)	6,805 (12.9%)	7,600 (12.4%)	7,950 (12.2%)	27,471 (12.8%)
Remote Australia	1,069 (3.0%)	1,541 (2.9%)	1,707 (2.8%)	1,980 (3.0%)	6,297 (2.9%)
Very Remote Australia	391 (1.1%)	541 (1.0%)	538 (0.9%)	183 (0.3%)	1,653 (0.8%)
School type – Small school					
No	32,201 (90.0%)	46,852 (88.2%)	54,437 (88.7%)	58,668 (89.8%)	192,158 (89.1%)
Yes	3,595 (10.0%)	6,280 (11.8%)	6,942 (11.3%)	6,660 (10.2%)	23,477 (10.9%)

NOTE: Numbers represent frequency (%).

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Visual inspection of WEC indexes showed no significant deviations from assumptions of normality. Table 2 shows derived indexes of well-being, engagement, and learning readiness. All three indexes show relative stability in means and variation year on year. Table 3 shows means and standard deviation of outcome measures NAPLAN and PAT for literacy and numeracy. No discernable patterns arise across the collection years.

Table 2. WEC Indexes by Data Collection Year

	Enrolment census year data used in the linkage				
	2016	2017	2018	2019	Total
N	35,796 (16.6%)	53,132 (24.6%)	61,379 (28.5%)	65,328 (30.3%)	215,635 (100.0%)
Overall WEC index	3.585 (0.618)	3.684 (0.627)	3.692 (0.580)	3.705 (0.571)	3.676 (0.597)
Well-being index	3.382 (0.792)	3.528 (0.813)	3.516 (0.739)	3.486 (0.744)	3.488 (0.769)
Engagement index	3.743 (0.626)	3.812 (0.631)	3.801 (0.598)	3.840 (0.590)	3.806 (0.609)
Learning index	3.411 (0.787)	3.524 (0.785)	3.634 (0.686)	3.645 (0.687)	3.573 (0.734)

NOTE: The numbers represent the mean (standard deviation) values.

Table 3. Outcome Measures (NAPLAN, PAT) by Data Collection Year

	Enrolment census year data used in the linkage				
	2016	2017	2018	2019	Total
NAPLAN N	17,518 (17.3%)	25,488 (25.2%)	30,158 (29.8%)	27,905 (27.6%)	101,069 (100.0%)
NAPLAN – Numeracy	553.15 (65.43)	524.94 (74.74)	523.80 (76.21)	527.34 (78.72)	530.12 (75.56)
NAPLAN – Reading	550.72 (69.60)	528.66 (79.39)	529.20 (81.24)	531.73 (76.40)	533.46 (77.94)
NAPLAN – Spelling	549.28 (75.60)	529.28 (80.81)	528.10 (81.33)	527.43 (79.69)	531.87 (80.18)
NAPLAN – Grammar/ Punctuation	546.05 (78.26)	522.09 (91.11)	526.41 (90.56)	524.56 (87.92)	528.20 (88.36)
NAPLAN – Writing	523.46 (78.98)	492.50 (88.53)	483.25 (87.62)	501.49 (86.00)	497.56 (87.06)
PAT N	34,774 (16.6%)	52,004 (24.8%)	59,942 (28.6%)	62,844 (30.0%)	209,564 (100%)
PAT – Mathematics	129.41 (11.27)	126.18 (12.52)	125.82 (12.58)	127.30 (12.96)	126.94 (12.54)
PAT – Reading	130.82 (12.34)	127.58 (14.04)	127.10 (14.30)	128.28 (14.54)	128.19 (14.06)

NOTE: The numbers represent the mean (standard deviation) values.

Table 4. Mixed Regression Estimates for WEC Indexes on Academic Outcomes Unadjusted and Adjusted

		NAPLAN										PAT			
		Numeracy		Reading		Spelling		Grammar		Writing		Reading		Mathematics	
		Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
WEC Index	Est	0.091	0.080	0.069	0.063	0.075	0.066	0.065	0.057	0.100	0.093	0.084	0.075	0.100	0.088
	95% CI	[.0864 .0966]	[.0749 .0848]	[.0638 .0751]	[.0578 .0688]	[.069 .0803]	[.0607 .0718]	[.0588 .0703]	[.051 .0622]	[.0947 .106]	[.0876 .0984]	[.0802 .0878]	[.0715 .079]	[.0963 .104]	[.084 .0912]
	N	93177	90483	94029	91321	94096	91383	94096	91383	94216	91493	204851	198713	204888	198788
Well-being Index	Est	0.056	0.042	0.008	0.010	0.014	0.016	0.006	0.010	0.033	0.044	0.028	0.028	0.065	0.051
	95% CI	[.0505 .0607]	[.0366 .0465]	[.00239 .0136]	[.00459 .0156]	[.00811 .0194]	[.0106 .0216]	[.000612 .012]	[.00432 .0154]	[.0276 .0388]	[.0389 .0497]	[.0245 .0322]	[.0247 .0322]	[.0611 .0685]	[.047 .0542]
	N	92908	90230	93752	91059	93824	91127	93824	91127	93944	91237	203910	197817	203944	197887
Engagement Index	Est	0.081	0.074	0.086	0.077	0.087	0.074	0.077	0.064	0.107	0.090	0.096	0.084	0.089	0.080
	95% CI	[.0763 .0866]	[.0694 .0793]	[.0803 .0916]	[.0711 .0821]	[.0809 .0923]	[.0685 .0795]	[.0711 .0826]	[.0588 .0699]	[.101 .112]	[.0843 .0952]	[.092 .0996]	[.0801 .0875]	[.085 .0923]	[.0768 .084]
	N	92402	89736	93251	90572	93313	90628	93313	90628	93439	90744	202902	196830	202928	196894
Learning Readiness Index	Est	0.129	0.119	0.101	0.091	0.118	0.105	0.104	0.091	0.149	0.137	0.101	0.088	0.130	0.119
	95% CI	[.124 .134]	[.115 .124]	[.0959 .107]	[.086 .0969]	[.112 .123]	[.0991 .11]	[.0989 .11]	[.0857 .0967]	[.144 .155]	[.131 .142]	[.0969 .104]	[.0846 .0919]	[.127 .134]	[.116 .123]
	N	92891	90212	93739	91046	93809	91111	93809	91111	93932	91224	203824	197735	203860	197809

Table 5. Mixed Regression Estimates for WEC Indexes on Academic Outcomes Adjusted, Stratified by Gender

		NAPLAN										PAT			
		Numeracy		Reading		Spelling		Grammar		Writing		Reading		Mathematics	
		Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
WEC Index	Est	0.083	0.079	0.075	0.054	0.082	0.053	0.064	0.051	0.119	0.073	0.083	0.068	0.091	0.087
	95% CI	[.0754 .0901]	[.072 .0853]	[.067 .0832]	[.0462 .0613]	[.0739 .0903]	[.046 .061]	[.0564 .0724]	[.0431 .0587]	[.111 .128]	[.0662 .0806]	[.0777 .0886]	[.0627 .0731]	[.086 .0967]	[.0826 .0923]
	N	45672	44618	46059	45069	46089	45101	46089	45101	46113	45187	100850	97436	100986	97369
Well-being Index	Est	0.043	0.042	0.022	0.001	0.031	0.005	0.018	0.003	0.072	0.026	0.037	0.019	0.054	0.051
	95% CI	[.036 .051]	[.035 .048]	[.0133 .0298]	[-.00598 .00882]	[.0228 .0396]	[-.0026 .0121]	[.0101 .0266]	[-.00419 .011]	[.0636 .0804]	[.0191 .0332]	[.0316 .0428]	[.0142 .0245]	[.0482 .0592]	[.0464 .056]
	N	45525	44512	45905	44961	45938	44996	45938	44996	45961	45083	100305	97085	100442	97012
Engagement Index	Est	0.078	0.072	0.086	0.069	0.087	0.063	0.069	0.062	0.108	0.075	0.089	0.080	0.083	0.080
	95% CI	[.0708 .0852]	[.0651 .0786]	[.0778 .0936]	[.0612 .0767]	[.079 .095]	[.0552 .0705]	[.061 .0768]	[.0539 .0698]	[.1 .116]	[.0677 .0824]	[.0835 .0941]	[.0742 .0848]	[.0781 .0885]	[.075 .0849]
	N	45243	44301	45632	44748	45658	44778	45658	44778	45683	44869	99835	96572	99956	96510
Learning Readiness Index	Est	0.115	0.124	0.093	0.090	0.110	0.100	0.093	0.089	0.157	0.120	0.087	0.090	0.117	0.124
	95% CI	[.108 .122]	[.117.131]	[.0853 .101]	[.0821 .0971]	[.102 .118]	[.0929 .108]	[.0852 .101]	[.0813 .0967]	[.149 .165]	[.113 .127]	[.0816 .0922]	[.0851 .0953]	[.112 .122]	[.119 .129]
	N	45507	44512	45889	44964	45920	44998	45920	44998	45946	45085	100261	97048	100396	96981

3.5 Model Results

All results are reported as standardized regression coefficients and should be interpreted as changes in standard deviation units of the outcome per single standard deviation unit increase in the independent variable. Standardization allows for direct comparison of effect sizes across different measures on the same outcome and different outcomes on the same measure. Effects with 95% confidence intervals not crossing the critical value of zero are considered meaningful.

Modelled relationships (Table 4) suggest weak effects of the overall WEC index on all learning outcomes with the effect size no larger than 0.1SD in all adjusted and unadjusted models. Broken down into the three constructs, the Well-being index has the least predictive power on academic outcomes with effect sizes in the hundredth of a standard deviation range. Engagement has a slightly stronger effect with most measures in the 0.08 to 0.10 range. Learning readiness has the largest effect sizes in the 0.1 to 0.15 range. All predictor and academic effect sizes estimated were positive and statistically meaningful, with no confidence interval crossing the critical value of zero.

Adjustment for various socioeconomic factors at the student, family, and school levels reduced the variance attributable to just the WEC instrument, but in no cases explained away meaningful effects, generally lowering predictor effect sizes by 10–20% whilst not significantly widening confidence intervals. Interaction effects of student year level and predictor, and census year and predictor were modelled (not shown) and no meaningful effects could be attributed to either interaction. This suggests that the relationship between WEC and academic achievement has been stable over time and over student year level. Due to the complex relationship between gender and academic outcomes as well as the differing trajectories that males and females have over the WEC instrument, stratification was used across genders to target different trajectories of WEC on academic achievement relationships. This was justifiable, as opposed to testing interaction effects due to the large sample size, allowing for strong predictive power even when splitting the sample in half, and the highly complex nature of differing gender trajectories across all adjustor covariates. Effect sizes (Table 5) for females tended to be lower than males in the overall WEC index. Individual construct indexes indicated much lower effects for females on the Well-being index, with a complete loss of meaningful effects for NAPLAN reading, spelling, and grammar outcomes. The Engagement index saw an overall stronger effect, but slightly lower for outcomes of NAPLAN literacy outcomes but not in NAPLAN numeracy or PAT outcomes. Learning readiness saw comparable results across genders.

4. DISCUSSION

In this study, we investigated how different aspects of well-being and engagement are connected to academic performance using what we believe to be the world's most extensive dataset linking well-being and academic outcomes in primary and secondary education. Our analysis showed that the Well-being Engagement Collection (WEC) index had a minimal impact on the National Assessment Program – Literacy and Numeracy (NAPLAN) and the Progressive Achievement Tests (PAT) outcomes. Delving deeper into the three WEC indexes, we found that emotional well-being had a negligible effect, engagement had a slightly more pronounced effect, and learning readiness exhibited the most significant influence on both NAPLAN and PAT scores. These findings emphasize the critical role of foundational concepts like perseverance, academic self-concept, and self-efficacy in the educational landscape. Each of these elements are integral to the broader framework of SRL (Schunk & Zimmerman, 2008). SRL refers to the ability of students to manage and take charge of their own learning processes, which includes setting goals, monitoring their progress, and adjusting strategies as needed (Schunk & Zimmerman, 2008). SRL has consistently been shown to contribute to a student's well-being, and overall academic success (Davis & Hadwin, 2021). However, it is worth noting that while LA has historically adopted SRL, its potential to support and foster the development of SRL actively has been somewhat underutilized (Viberg et al., 2020). This suggests an opportunity for educators and researchers to leverage LA not just as a diagnostic tool, but as a means to enhance and cultivate SRL skills among students.

Interestingly, when we examined the interaction between the predictor variables and student year level, as well as the predictor and census year, the results did not yield any significant findings. This suggests that the relationship between the WEC index and NAPLAN/PAT scores remains relatively consistent across different year levels and census years, which is consistent with previous research on NAPLAN trends (McGaw et al., 2020; Thomas et al., 2023). However, there is recent evidence that the COVID-19 pandemic has had a detrimental effect on student emotional well-being (Di Pietro, 2023). The sudden shift to remote learning forced students to adapt to new learning environments, technologies, and teaching methods (Hughes, 2020). The extended periods of isolation, uncertainty, and anxiety took a toll on student mental health, largely stemming from disruptions in their educational routines, physical activities, and chances for social interaction (Jiao et al., 2020). Future research could delve into how these emotional changes might have affected their academic performance from 2020 onwards.

Our stratified models, which accounted for gender and adjusted for socioeconomic factors, revealed a more pronounced effect of the WEC index on academic outcomes for males compared to females. This was consistent across all academic domains, except for numeracy. Specifically, Emotional Well-being had a notable impact on literacy outcomes for males in both NAPLAN and PAT. However, this effect was entirely absent for females. This raises a question: Could it be that girls possess a robust academic self-concept in literacy, rendering their emotional well-being less influential on their academic performance? In line with Pekrun's Control Value Theory, previous research indicates that girls generally develop a higher self-concept in verbal domains and have more favourable attitudes towards reading compared to boys (Frome & Eccles, 1998; Lazarides & Raufelder, 2021; Logan & Johnston, 2009; Pekrun, 2006). Similarly, evidence suggests that teacher biases may negatively affect boys' self-concept regarding reading, while not influencing girls in the same way (Retelsdorf et al., 2015). Furthermore, this positive reading self-concept in girls might be observable as early as first grade (Fives et al., 2014). There is also the potential explanation that NAPLAN may not affect students as negatively as once portrayed, but this hypothesis warrants further exploration in future research endeavours. In terms of Engagement, the effect was more pronounced for males, but remained largely consistent across genders, which is in line with previous research (Huang, 2013; McGeown et al., 2012). Learning readiness, on the other hand, exhibited an equal influence on academic outcomes for both males and females. Here again, our results emphasize that constructs linked to SRL, such as self-concept and perseverance, play a pivotal role in academic success for students irrespective of their gender. In fact, SRL has consistently been shown to be one of the most robust predictors of academic achievement (see, for example, Ohtani and Hisasaka's [2018] meta-analysis).

This study advances our understanding and insights into the relationship between student well-being and academic outcomes. While the correlation between the WEC and standardized assessment was limited, it does highlight the importance of developing student SRL proficiency (learning readiness). The integration of SRL into LA systems has a significant history, evolving from initial research focused on cognitive metrics to incorporating non-cognitive factors like SRL. Researchers such as Winne and Hadwin (1998) have been pivotal in this integration, positing that learners actively engage in a series of interconnected phases to manage and optimize their learning processes (Winne & Hadwin, 1998). This foundational theory underscores the dynamic nature of SRL and its importance in LA (Gašević et al., 2015). As such, the findings underscore the potential for incorporating LA methodologies as evaluative tools and proactive means to enhance student SRL proficiency. However, the current literature often focuses on university students, who are more mature and established learners, leaving a gap in understanding how these methodologies apply to primary and secondary school students (Ifenthaler & Yau, 2020; Pardo et al., 2015). The novelty and challenge here for LA research is to identify the stage in which SRL skills are learned or set.

Winne and Hadwin's (1998) SRL theory, which is commonly adopted in LA, posits that learners actively engage in a series of interconnected phases to manage and optimize their own learning processes. This theory has been integrated into LA to enhance understanding of how students regulate their learning (Gašević et al., 2015; Schumacher & Ifenthaler, 2018). However, it is also imperative to identify the temporal dimensions of SRL development and establishment. Students with high levels of SRL proficiency readily adapt and change study approaches to best complement the task and standards required. At what point do students develop or establish a portfolio of learning strategies that can be drawn upon as circumstances require? Identifying when and how SRL skills take root and solidify in learners is crucial. While much of the current LA research focuses on identifying SRL skills, understanding the developmental trajectory of these skills is equally important (Pardo et al., 2015). The educational landscape benefits significantly from discerning whether SRL skills are static attributes or dynamic competencies that evolve and adapt throughout a learner's educational journey.

The identification of emotional well-being's gender-specific impact on literacy outcomes also emphasizes the need for a more nuanced approach in educational research. Prior LA research emphasizes the importance of personalized learner models to cater to individual needs (Tsai et al., 2020). These authors suggest that learner empowerment should occur through the interaction between LA systems and students. Furthermore the authors' approach enables the identification of unique needs and the provision of tailored interventions, thus supporting agency, academic performance, and emotional well-being (Tsai et al., 2020). The study contributes to our understanding of the intricate interplay between well-being and academic success and provides insights for advancing our approach towards establishing a more holistic and tailored educational experience for all students.

4.1. Limitations and Future Research

One of this study's key strengths resides in using a very large data set. However, we need to acknowledge some limitations. Our study was based on cross-sectional data and was correlational in nature, which inherently limits our ability to draw causal inferences. Future studies can explore trends over multiple years and follow students longitudinally. Another limitation pertains to the WEC index itself. While it offers a comprehensive measure of well-being at a population level, it is not domain specific. For instance, learning readiness is a broad concept and does not cater to specific academic domains. This is where LA could be complimentary, as it can provide domain-specific insights that might address such limitations. Furthermore, while we used NAPLAN as a measure of academic achievement, we recognized the inherent limitations of high stakes standardized tests (Au, 2022) and this prompted us to include PAT in our analysis.

Another potential limitation is the lack of data on the impact of the COVID-19 pandemic, which could have influenced academic outcomes (Hoofman & Secord, 2021). The pandemic's varying effects across different demographic groups might have introduced further variability in our findings, which we were unable to capture due to the data's scope and nature. However, looking ahead, there is a pressing need for system-wide data collection on academic achievement beyond standardized tests. Furthermore, the integration of LA can provide a transformative approach to this research. With its capability to process vast amounts of data and identify patterns, LA can offer deeper insights into the relationship between socio-emotional constructs and academic performance. By leveraging LA, researchers can track real-time student interactions, behaviours, and engagement, offering a more comprehensive view of how well-being directly or indirectly affects academic outcomes. This integration fills the gaps in the current literature and paves the way for more personalized interventions and support mechanisms for students based on their unique socio-emotional and academic profiles.

4.2. Implications for Policy and Practice

The implications of the study's findings for student learning, policymaking, and school systems are significant. These findings can be leveraged to enhance student learning by implementing personalized and adaptive learning models tailored to individual needs. For instance, integrating LA systems can help identify specific areas where students struggle, enabling educators to provide targeted interventions that improve both academic performance and emotional well-being (Gašević et al., 2015; Ifenthaler & Yau, 2020). Additionally, learner profiles (LP) that incorporate well-being and engagement measures can complement traditional grades, offering a more comprehensive view of student development (Barthakur et al., 2023). This holistic approach ensures that students' socio-emotional skills are nurtured alongside their academic achievements (Barthakur et al., 2023). For policymakers, these insights can inform decision-making by highlighting the importance of addressing socio-emotional factors in educational strategies. This could lead to the development of policies that support holistic educational approaches, incorporating both academic and well-being metrics into school evaluation systems. Furthermore, differences in findings based on gender should be considered by policymakers and school systems to ensure that educational strategies are inclusive and equitable. Recognizing and addressing these gender-specific impacts can lead to more tailored and effective interventions, promoting better outcomes for all students. These considerations emphasize the need for policies that support diverse learning needs and foster an environment where every student can thrive.

5. CONCLUSION

Our study analyzed the relationship between the WEC index and academic outcomes, specifically NAPLAN and PAT scores. We found that the WEC index had a minimal overall impact on these scores. Among the WEC components, learning readiness showed the most significant influence. The relationship between the WEC index and academic scores was consistent across different student year levels and census years. Notably, the WEC index had a more pronounced effect on academic outcomes for males, especially in literacy, than for females. This observation suggests potential differences in how emotional well-being influences academic performance between genders. Future research should consider leveraging LA for a more in-depth understanding of the interplay between socio-emotional constructs and academic performance, potentially leading to more personalized student interventions.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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