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INTRODUCTION

This article takes a fresh look at learning analytics to consider the learning needs of neurodivergent students. Many neurodivergent students have 'executive dysfunction,' leading to problems planning, prioritising and organising their study. First, current research linking executive function (EF) of the human brain with taught strategies known as "self-regulated learning" (SRL) is used to establish a connection between these disparate fields of research. Then SRL interventions used in a classroom setting are considered in a computer-based learning environment. Finally, recent research in these fields is brought together into recommendations for design of a new learning analytics tool.

MEETING THE NEEDS OF NEURODIVERSE LEARNERS

Mirroring our natural genetic diversity, as humans we are also neurologically diverse. While the term "neurodiverse" was first coined by the autism community to differentiate themselves from the "neurotypical" mainstream, it now encompasses numerous conditions that can affect learning, including: attention deficit hyperactivity disorder (ADHD), ASC (autism spectrum conditions), dyslexia, dyspraxia, dyscalculia, dysgraphia, Irlen Syndrome and SLI (specific language impairment). The neurodiversity movement recognises that neurodivergent individuals bring strengths, often taking different approaches, with unique, creative problem-solving abilities (Rentenback et al., 2017). Currently in tertiary education, neurodivergent learners are grouped with our disabled learners. This is because, under a "social model of disability," they are disabled by the many challenges and barriers they experience to their learning under the current education system (ACHIEVE & TEC, 2021, p. 16).

As educators, we need guidelines to help us enable our neurodivergent learners to achieve their potential to make valuable contributions to our educational institutions, communities and their future workplaces. Current, research-informed guidelines are to follow the three principles of Universal Design for Learning (UDL) (International Disability Alliance, 2021, p. 16). The three UDL principles involve providing students with different options for:

1. Representation – for example, in display of content, using different types of media (audio, video, text) and visual aids
2. Action & Expression – how the student interacts with instructional materials, and demonstrates their learning for assessment purposes
3. Engagement – to show the 'why' or relevance of the learning, to keep students motivated, engaged and developing skills in self-regulation (Meyer et al., 2014; CAST, 2018).

These principles are mirrored in Mirfin-Veitch and colleagues' (2020) detailed overview of the learning needs of neurodivergent learners, with recommendations to:

1. Adapt learning environments for inclusivity (physical as well as relational environments, with care taken with timetabling, time structuring of instruction, and extra time allocation, where needed)
2. Adapt curriculum and the instructional or learning and teaching methods used – for example, using UDL
3. Embed classroom strategies to create safe, inclusive learning environments, with an emphasis on relationship-building (tutor and peers) with neurodivergent learners
4. Promote student agency, self-regulation skills and strategies, and self-management of behaviour (Mirfin-Veitch et al., 2020).

There is much learning design work yet to do at the level of programmes and courses to address the first two points. However, for the latter two points, efforts are often limited to time spent in the classroom and by the finite resource of our teaching and learning support staff. As more time is spent learning online, we need to better harness technology to offer neurodiverse learners the extra support they need to plan their learning, manage time and develop all-important skills in self-regulation and behavioural management.

THE CURRENT STATE OF PLAY

To date, innovations in the use of computer-based learning environments (CBLE) to support neurodiverse learners have been surprisingly limited (Mirfin-Veitch et al., 2020, pp. 25–26). There are various freely available assistive technologies and accessibility tools (for example, for authoring online content), and diagnostic (for example, for dyslexia) and proprietary (pay-for-access) software, which are outside the scope of this article.

Instead, this section will briefly describe the current state of learning analytics in the author's institution's learning management system (LMS), Moodle. Moodle is an open-source eLearning platform, enticingly allowing for potential collaborative design and development innovations (Christie, 2022). However, learning analytics are underutilised. Vast amounts of data from students' day-to-day interactions are collected on computer servers. This big data approach contributes to an underground aquifer of untapped information. Valid concerns around consent, surveillance, student privacy and data security have restricted our use of learner analytics to date. Also, designing suitable 'bore holes' to tap into this vast aquifer depends on the questions we wish to ask, who is asking them and the purpose of interrogating this data set.

A traditional 'by student' approach is to use learner analytics to identify at-risk students. For example, a pilot research project is underway in the University of Canterbury's Moodle LMS to identify at-risk students and to notify relevant staff (personal communication, Rachel Cash). Goode and colleagues caution against a 'by class' approach to use learner analytics to compare teaching from a performance review approach (Goode et al., 2021). Indeed, learning analytics should never be used as an evaluative performance measure of either staff or students, and care must be taken not to collect data that may be used to perpetuate existing societal biases or inequities (Selwyn, 2019; Goode et al., 2021).

Learning is a key part of learning analytics, and should be a primary driver in the design of such a system (Gašević, 2015; Selwyn, 2019). Learning differences and support needs of neurodivergent learners are varied, but all learners across the neurodiversity spectrum can benefit from the development of self-regulated learning (SRL) skills and strategies (Meyer et al., 2004; Mirfin-Veitch et al., 2020). SRL is a learned skill that can improve student performance (see Zimmerman, 2008 and references therein).

WHY NEURODIVERGENT LEARNERS BENEFIT FROM SELF-REGULATED LEARNING

This section explores the connection between self-regulated learning, executive function and neurodiversity. A shared feature of neurodivergent brains are differences in executive function, which controls processes such as planning, goal setting, organising, memorising, starting or changing an action, and self-evaluating. These executive processes occur in distinct areas ('nuclei'), largely found in the prefrontal cortex (Pennington, 1997), but also scattered throughout the cortex and subcortical brain regions (Bernstein & Waber, 2007). The executive function circuitry integrates information from past and present to inform future plans, which is held in the "working memory" (Hofmann, Schmeichel & Baddeley, 2012); imagine a two-way traffic system between nuclei in the frontal cortex and relevant subcortical areas (Bernstein & Waber, 2007).

Many of our neurodivergent learners (10–15 percent) have dyslexia, which is traditionally associated with reading and writing difficulties. People with dyslexia also score significantly lower in executive function tests, particularly of their working memory (Varvara et al., 2014). Like dyslexia, ASC and ADHD are also neurodevelopmental conditions. A meta-analysis found that, compared with neurotypical controls, people with ASC showed lower levels of performance in all executive function domains, particularly working memory, concept formation, response inhibition, fluency and planning (Demetriou et al., 2018).

Similarly, Willcutt and colleagues found that people with ADHD showed lower levels of performance in all executive function domains, most significantly in their working memory, response inhibition, vigilance and planning (Willcutt et al., 2005). The authors conclude that while executive dysfunction plays a major role in characteristic behaviours of ADHD, such as distractibility, impulsivity and inattention, it may not be causative of this strongly heritable condition (Willcutt et al., 2005). Importantly, 5.3 percent of children have diagnosable ADHD, but this decreases to 2.5 percent of adults (Faraone & Larsson, 2019). This shows that, as people with ADHD approach adulthood, there is a restoration of executive function, speculatively due to a combination of learnt strategies and neurocognitive compensatory mechanisms, or a removal of stimuli causing pathological stress in ADHD brains in childhood and adolescence (Hess et al., 2018).

A literature search for learnt strategies to enhance executive function leads directly to teaching students to become self-regulated learners (Schmitz & Wiese, 2006; Stoeger & Ziegler, 2007). Self-regulated learning has three subdomains:

1. Metacognition – of the mind. Metacognition involves knowledge about how one thinks and learns, leading to control and monitoring of one's thinking and learning strategies (Dinsmore et al., 2008; Roebers, 2017)
2. Self-regulation (SR) – of the interaction between self and environment. SR is broadly defined as goal-directed behaviour, with active monitoring of one's thoughts, emotions and behaviours; one's motivation and one's capability to achieve the set goal (Hofmann et al., 2012)
3. Self-Regulated Learning (SRL) – this is the application of metacognition and SR in an academic setting; that is, the choice and deployment of different study skills and strategies to achieve learning goals, with self-evaluation and a help-seeking component (Zimmerman, 2002).

Each of the above terms has a common metacognitive core whereby self-aware individuals use monitoring to gain control over their thoughts and actions (Dinsmore et al., 2008, p. 405).

ESTABLISHING THE LINK BETWEEN EXECUTIVE FUNCTION AND SELF-REGULATED LEARNING

In the following section, I will show that executive function and self-regulated learning have considerable overlap, and that executive function processes lead to self-regulated learning. That is, SRL is an application of executive function in an academic setting. Educational research is often fragmented, with different researchers using different terms for quite similar concepts. This divergence is seen with the concepts of executive function, which is rooted in neuroscience, and self-regulated learning, which has grown out of educational psychology and been developed by social cognitive scientists such as Albert Bandura. Recently, researchers have joined the dots between EF and SRL. Miyake and colleagues (2000) used latent factorial analysis to clearly define three executive function processes:

1. Working memory (planning, prioritising, initiating and memorising)
2. Inhibition (focusing, avoiding distractions and impulsive behaviour)
3. Task-switching (also called "shifting").

Hofmann and colleagues (2017) examined these processes under a self-regulation lens and concluded that all these processes led to self-regulation. Hence executive function "subserves" self-regulation, which, broadly speaking, is goal-directed behaviour (Hofmann et al., 2017, p. 4):

1. When setting out to achieve a goal, the working memory needs to hold all possible options, integrate this knowledge with the current context and select an optimal strategy, then maintain the strategy until the goal is completed
2. Inhibitory processes are needed to keep an individual on task and on track
3. Task-switching may be required – for example, to stop and eat, then to return to achieving the set goal.

Hence strong executive function serves up good self-regulated behaviours. In contrast, metacognition is the "master" that exercises control over executive processes (Roebers, 2017). For example, we can learn new strategies to enhance our working memory, then use metacognitive strategies to monitor and control use of these. As illustrated by the author, each executive function process has a monitoring–control metacognitive loop (see Figure 1). In the figure, self-regulated learning with its metacognitive monitoring–control loop is shown at the same level as, but distinct from the three EF processes.

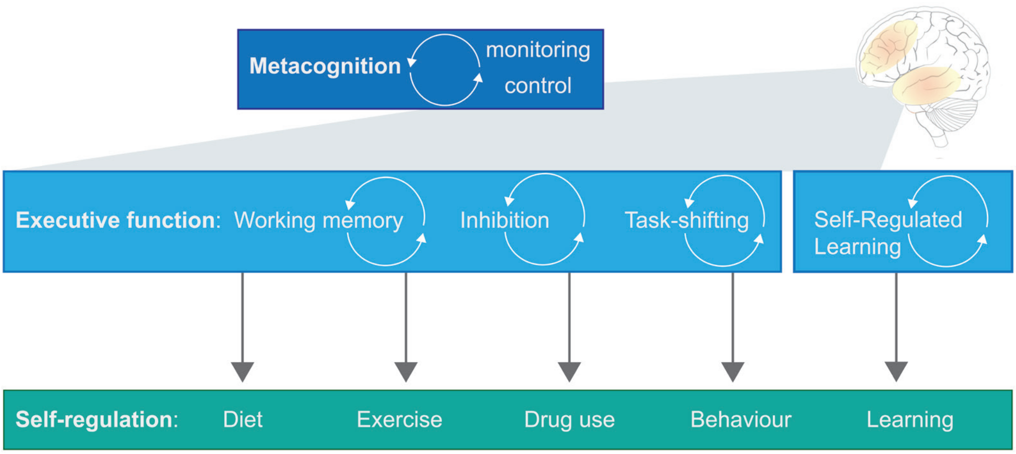

Figure 1. Schematic by the author to show the hierarchy of metacognition, executive function and self-regulated learning. Metacognitive processes of monitoring and control (shown as curved arrows) are used to attain mastery over EF processes (Roebers, 2017) and SRL strategies (Dinsmore et al., 2008). Hofmann et al. (2017) describe how the EF processes in turn subserve self-regulation, which is exerted in the different contexts shown.

Each executive function process contributes to self-regulation (SR), a phenomenon which has been researched in many contexts, from control of diet to alcohol and drug use. Here we are primarily concerned with SR in the academic context, which can be taught through SRL and leads to learning.

Effeney and colleagues (2013) attempted to test empirically whether self-regulated learning is a "contextualised application" of executive function. They studied both constructs in adolescent males, at different ages, in an Australian all-boys high school. They found that the boys' self-reported measures of EF and SRL were strongly correlated. Measures of executive function are known to increase during adolescent development, and the boys' self-regulated learning scores closely followed the EF increases, suggesting adoption of learnt SRL strategies as they progressed in the strongly academic setting. While their results confirm a close overlap of the EF and SRL constructs, the study size was too small to draw conclusions around directionality, and the authors raised concerns about the weaknesses of retrospective self-regulated learning surveys (Effeney et al., 2013).

Importantly, the convergence of the previously separate executive function and self-regulated learning research fields allows EF and education researchers to tap into the vast literature on SRL in computer-based learning environments (CBLE).

SELF-REGULATED LEARNING AS AN INTERVENTION

The focus of this article now returns to how to use learning analytics to guide development of self-regulated learning. Can we use CBLE to make contextualised suggestions about when to use certain strategies over others? Can students engaged in self-directed learning use self-monitoring tools in CBLE to better control their learning?

There is good evidence that classroom interventions are effective in developing self-regulated learning at university level (Schmitz & Wiese, 2006) and at primary school (Stoeger & Ziegler, 2007). The challenge is to transfer SRL interventions into a CBLE, to support and guide neurodivergent learners who may have lower scores in working memory (motivation; time management; planning); inhibition (hence decreased attention spans), task switching and their overall self-regulation abilities (Mirfin-Veitch et al., 2020; Alasalmi, 2021).

Zimmerman acknowledges that different self-regulated learning strategies are activated at the beginning (forethought), middle (performance) and end (self-reflection) in a sequence of learning (Zimmerman, 2002, 2008). Schumacher and Ifenthaler (2018) found that many of students' expectations of learning analytics spanned Zimmerman's three distinct learning phases:

1. Forethought phase: Requires tools for scheduling, planning (for example, checklists), maintaining motivation, personalising recommendations and for setting goals (for example, clear learning outcomes and objectives)
2. Performance phase: Requires tools to assess competency and skill development, such as auto-marking quizzes, recognition of offline and social learning, and opportunities for self-assessment
3. Self-reflection phase: Requirement for results of assessments with timely and valid feedback, and a learning management system-wide awareness of a student's "current state of knowledge, their activities in the system as well as their progress towards own or set learning objectives" (Schumacher & Ifenthaler, 2018, p. 70).

Based on promising research using self-regulated learning in computer-based learning environments, there are good indications that students can be guided towards SRL using learning analytics. Selected studies are described below so a picture of a future learning analytics system might emerge:

- Not surprisingly, only certain learning analytics data are positively correlated with student achievement. These are: number of logins, interaction with online activities and participation in discussion forums (Gašević et al., 2015). The display of distracting, redundant information, such as time spent online, should be avoided.
- Use of specific, task-related tools such as Turnitin's similarity checker was positively correlated with achievement in a writing task (Gašević et al., 2015). SRL tracking should incorporate measures of students engaging with specific, task-related tools.
- Hadwin and colleagues found that students' "metacognitive monitoring" can be tracked by plotting transition graphs and measured using graph density (Hadwin et al., 2007). Importantly, the metacognitive monitoring

scores *decreased* when students were less invested in the task. The recommendation is to follow metacognitive monitoring, as it is a central SRL process – but note that this needs coupling with measures to assess the quality of student work produced (Gašević et al., 2015).

- In regard to the above point, promising advances have been made using Coh-metrix text analysis to automate assessment of students' writing for cohesiveness and comprehensibility (McNamara et al., 2014). This opens up the potential for students to receive feedback on their writing, prior to assessment submission, where feedback has been a major expectation of students from a learning analytics system (Clouder et al., 2017; Schumacher & Ifenthaler, 2018). Self-regulated learning tracking should compare the SRL strategies used with student achievement data, and ensure that the student need for automated feedback is met.

FURTHER CONSIDERATIONS FOR DESIGN OF A LEARNING ANALYTICS TOOL

How this learning analytics data will be displayed, accessed and visualised by students is another active area of research (Verbert et. al., 2013). While Verbert and colleagues describe fully customisable dashboards, Zimmerman (2008) envisions heat maps to guide a student's SRL choices. There is the prospect of even more accessible options, such as a Moodle ChatBot (Karmali, 2018).

Taking a student-centred approach, the first consideration in design of a learning analytics tool is that it keeps learning at the forefront. One way to achieve this is to develop students' skills as self-regulated learners (Zimmerman, 2002, 2008), as expanded upon in this article. Secondly, a learning analytics tool should be co-designed in partnership with students, in particular with disabled students as described in the redeveloped Kia Ōrite Toolkit (ACHIEVE & TEC, 2021). Thirdly, a learning analytics tool needs to be accessible, customisable and optional for students. Rangatiratanga is the fourth pillar of Angus Macfarlane's Educultural wheel (2004), alongside manaakitanga (an ethic of caring), whanaungatanga (relationship building) and kotahitanga (unity and togetherness). In political terms, rangatiratanga is the right to exercise authority, independence and self-determination and, in an educational context, has come to mean student autonomy and exercise of agency (Macfarlane, 2004). Applying the rangatiratanga principle to learning analytics, a student should be able to opt in, as Selwyn states: "rather than students being permitted to 'opt-out' of using learning analytics systems during their school or university studies" (Selwyn, 2019, p. 16).

Rātima and colleagues place the student's wellbeing, oranga, at the centre of the Educultural wheel (2022). A powerful model emerges where a student becomes a co-designer in their learning experience and leads to increased student agency, ownership of learning and enhanced student wellbeing (Rātima et al., 2022).

CONCLUSIONS

Surveys of students spanning the neurodiverse spectrum show they have realistic, valid expectations of learning analytics that support their learning (Clouder et al., 2017; Schumacher & Ifenthaler, 2018; Alasalmi, 2021). In our bicultural context of Aotearoa New Zealand, we need to move away from traditional 'performative' models of learning analytics towards a 'formative' model that guides and supports learning for all students.

As proposed in this article, a learning analytics tool should be co-designed in partnership with students, including neurodivergent and disabled students, who should be financially compensated for this work (Kia Ōrite Toolkit). This – the author hopes – could lead into an exciting collaborative project to design a prototype feature or plug-in for Moodle.

In the classroom, the learning differences of our neurodivergent learners need to be understood, acknowledged and accommodated by empathic and compassionate teachers. Similarly, learning designers and educational software developers need to cater first to our underserved learners, who are often disabled by the learning environments they must operate within. The adage that what is good for disabled learners is good for all applies equally in computer-based learning environments.

Amy Benians joined Te Ama Ako, the Learning and Teaching Development team at Otago Polytechnic (OP), in August 2018. She supports staff to design, develop and deliver blended and online courses using educational technologies. Prior to this, she worked as a research scientist, lecturer, scientific writer and instructional designer. She holds a PhD in clinical pharmacology from the University of London and a Graduate Diploma in Tertiary Education (GDTE) from OP. Her research interests include teacher professional learning and development within communities of practice, learning analytics, neurodiversity and student-centred learning and teaching.

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