

COVID-19's impact on learning processes in Australian university students

Darrell Eckley¹ · Andrew Allen¹ · Prudence Millear¹ · Karina Tirsvad Rune¹

Received: 8 May 2022 / Accepted: 31 October 2022 / Published online: 17 November 2022 © The Author(s), under exclusive licence to Springer Nature B.V. 2022

Abstract

The novel coronavirus SARS-CoV-2 (COVID-19) has accentuated the role and interplay of numerous educational factors, inviting pedagogical research concerning online education. Using self-determination theory's basic psychological needs and fundamental learning theories, identified educational factors were integrated into three pathways: (1) autonomy, technology acceptance, and self-regulation of learning; (2) relatedness, authentic happiness, and a classroom community; and (3) competency, harmonious passion, and trait conscientiousness. This study extends educational research by elucidating the relationships between psychological need fulfilment, educational factors, and students' expectations of their future grades during the impact of COVID-19. Australian university students (N=226, 77% female) completed questionnaires assessing their experience of home isolation, factors of each hypothesised pathway, and their expected grades. Structural equation modelling revealed that higher need fulfilment significantly predicted engagement in educational factors and that educational factors are complexly interrelated, providing resilience, motivation, and the mechanisms that facilitate learning. Most importantly, relatedness between academics and students positively influenced all learning pathways. Reciprocal determinism demonstrated the most substantial association with expected grades, and new insight was gained into the interrelationships of passion, trait conscientiousness, and self-regulation of learning.

Keywords COVID-19 · Education · Psychological needs · Self-determination theory

1 Introduction

COVID-19's Impact on Learning Processes in Australian University Students.

Andrew Allen aallen2@usc.edu.au

¹ School of Health and Behavioural Sciences, University of the Sunshine Coast, 90 Sippy Downs Drive, Sippy Downs, QLD 4556, Australia

Knowledge acquisition, knowledge processing, and internalisation of knowledge occur through processes that are primarily accomplished by students' interactions with information, academics (i.e., teachers, tutors, lecturers, or scholars), and peers in a social learning environment (Bandura, 1977; Piaget, 1973; Vygotsky, 1978). Typically, changes to this learning environment have occurred incrementally; as technologies develop, academics have embraced an active learning approach facilitated by universities increasing investment in digital infrastructure (Aithal & Aithal, 2019; Dziuban et al., 2018; Tucker, 2012; Williamson, 2020). In contrast to this incremental environmental transition, the COVID-19 pandemic declaration of March 2020 was the catalyst for public health strategies that brought about sudden and unexpected change (Department of Health, 2020; World Health Organisation, 2020). Within days, face-to-face interaction on purposefully designed university campuses transformed into virtual interactive meetings with staff and students from home isolation. As yet, no published studies have assessed the unique impact of this transformation on the processes of learning.

Active learning is a function of distinct and complex relationships between diverse variables (Elen & Clark, 2006), the interaction between the student and external stimuli, the internal processes of knowledge construction, and the motivational forces that drive both (Illeris, 2018). Typically, educational research has attempted to simplify this complexity through a reductionist approach, often examining the unique contribution of a single educational factor (Elen & Clark, 2006). However, reductionism "generally signifies a loss of complexity which hinders an adequate understanding of reality" (Wrigley, 2019, p. 146). Therefore, to gain a more nuanced understanding of COVID-19's complex impact within the expanding digital domain a holistic model of investigation is suggested, initiated by motivational forces and aligning educational factors in learning pathways according to the principles of classic learning theories.

One critical factor that applies to all learning is a student's motivation (Thoonen et al., 2011; Chen & Jang, 2010). Self-determination theory (SDT; Deci & Ryan, 2000) posits that a student's optimal functioning (a self-motivation to achieve growth; Maslow, 1943) requires specific support from their educational environment to fulfil three basic needs: autonomy, relatedness, and competency (Niemiec & Ryan, 2009). Given that learning is broadly defined as "any process that in living organisms leads to permanent capacity change and which is not solely due to biological maturation or ageing" (Illeris, 2007, p. 3), it may be considered analogous to growth. Therefore, it is feasible that the basic psychological needs required to motivate growth would align with the processes of learning that better facilitate growth. Autonomy, defined as an independent and active involvement in learning that is regulated by the self (Niemiec & Ryan, 2009), is consistent with psychological constructivism. Relatedness, a feeling of being genuinely liked, respected, and valued by educators and colleagues (Niemiec & Ryan, 2009), is consistent with social learning principles. Finally, competency, a feeling of efficiency, effectiveness, and self-efficacy in one's studies (Niemiec & Ryan, 2009), is consistent with the principles of co-construction of knowledge within the zone of proximal development of social constructivism.

1.1 Psychological constructivism: the autonomy pathway

Psychological constructivism (Piaget, 1973) holds that individuals must actively construct their knowledge through the interaction of prior learning and new information. During COVID-19's restrictions, students were forced to access new information primarily online, possibly accentuating behaviours related to their readiness to use the required technology (e.g., the technology acceptance model; Davis et al., 1989) and their engagement in cognitive strategies to regulate their learning more independently (e.g., self-regulation of learning; Zimmerman, 1990). Thus, both factors may be valuable in actively constructing knowledge in online environments.

The autonomy pathway comprises the elements of autonomy, technology acceptance, and self-regulation of learning, and their influence on expected grades during and beyond the COVID-19 lockdown (see Fig. 1). Autonomy support is derived from academics' support of a student's independent and active involvement in learning through classroom environments that nurture students' preferences, interests, and internal motives (Dickinson, 1995; Reeve et al., 2004). In education, research has demonstrated autonomy-supportive measures by academics to be associated with self-regulation of learning by secondary school students (Wang et al., 2016), and that self-regulation skills predict academic performance at university (Broadbent & Fuller-Tyszkiewicz, 2018; Xiao et al., 2019). Studies of university students also support the notion that the association between autonomy support and self-regulation of learning may be mediated by technology acceptance (Liaw & Huang, 2013; Nikou & Economides, 2017). However, the potential for technology acceptance to fully mediate the relationship between autonomy support and self-regulation of learning has not been directly examined. COVID-19's lockdown may have challenged a student's feelings of autonomy and their ability to access information through new

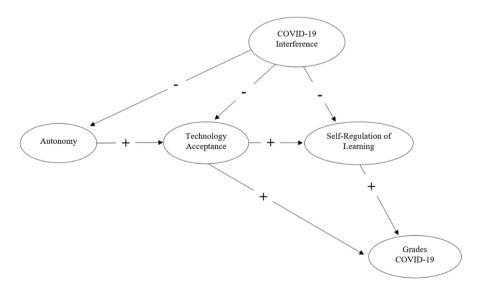


Fig. 1 The autonomy pathway

virtual platforms. Thus, the construction of personal knowledge through self-regulation strategies may have been reduced (Pelletier et al., 2002; Rocchi et al., 2013).

1.2 Social learning: the relatedness pathway

In contrast, social learning theories emphasise the importance of social interactions to model learning through observation (Bandura, 1977) and continuous interaction between an active learner and the persons, objects, and symbols in their immediate environment (Bronfenbrenner, 1979; Bronfenbrenner & Ceci, 1994). During the COVID-19 lockdown, social interaction existed primarily and almost solely on virtual platforms, resulting in reduced social interactions and, in turn, diminished psychological wellbeing (Cao et al., 2020; Wang & Zhao, 2020). Therefore, the extent that impediments to social interactions affected active learning may be a function of students' resilience in emotional stability (e.g., authentic happiness; Seligman, 2004) and sense of belonging and trust (e.g., classroom community; Rovai, 2001).

The relatedness pathway comprises the elements of relatedness, authentic happiness, a classroom community, and their influence on expected grades during and beyond the COVID-19 lockdown (see Fig. 2). Relatedness support is derived from academics' use of processes that enhance a student's sense of interpersonal connection, such as video conferencing, group assignments, encouraging questioning, and emotional support (Niemiec & Ryan, 2009). Educational research indicates that the formation of a classroom community in online university students can be predicted by relatedness support (Booker, 2008; Rovai, 2001). Moreover, authentically happy people more readily accept diversity and create inclusive social groups that may contribute to a sense of community (Dunn & Schweitzer, 2005; Morcom & Mac-Callum, 2012). However, only research outside the educational domain associates

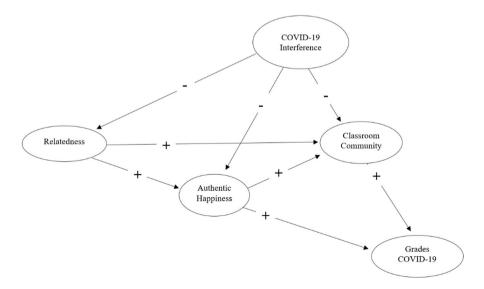


Fig. 2 The relatedness pathway

happiness with an increased sense of community (i.e., neighbourhood community; Ross et al., 2019). When a classroom community forms, student retention, engagement, and knowledge sharing increase, assisting academic success (Booker, 2016; Yilmaz, 2016), although the direct effect on grades remains controversial (for review see Beachboard et al., 2011; Boydie, 2020). Therefore, in theory, it is feasible that authentic happiness may mediate the relationship between relatedness support and the development of a classroom community (e.g., King, 2015; Ross et al., 2019). COVID-19's physical restrictions forced students to study from home isolation; thus, an individual's feeling of relatedness, happiness, and sense of community may have diminished by the lack of in-person classroom contacts (Cao et al., 2020; Santini et al., 2020; Wang & Zhao, 2020).

1.3 Social constructivism: the competency pathway

Social constructivism (Vygotsky, 1978) posits that individuals learn when knowledge is co-constructed with support from others in a zone of proximal development. "What the child is able to do in collaboration today, he will be able to do independently tomorrow" (Vygotsky, 1987, p. 211). During the lockdown, the academic's crucial role in the co-construction of knowledge may have been impeded by the online environment, necessitating more student independence in learning. Therefore, how readily students adapted to this independence may be a function of factors associated with persistence (e.g., harmonious passion; Vallerand et al., 2003) and conscientiousness (e.g., trait conscientiousness; Costa & McCrae, 1992).

The competency pathway comprises the elements of competency, harmonious passion, trait conscientiousness, and their influence on expected grades during and beyond the COVID-19 lockdown (see Fig. 3). Competency support in an online

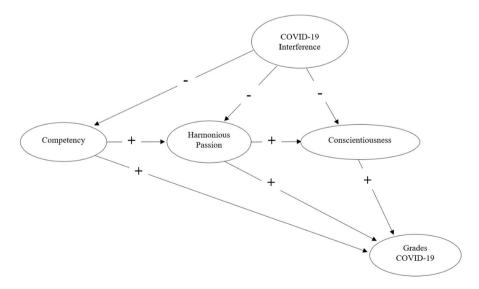


Fig. 3 The competency pathway

environment is derived from academics' support of a challenging but achievable experience through classroom environments that provide optimal challenges with positive feedback (Niemiec & Ryan, 2009). Studies have demonstrated that competency support directly predicts university students' academic success (Nahyun & Hana, 2017; Sulea et al., 2015; Talsma et al., 2018; Trautwein et al., 2009) through the process of reciprocal determinism (a reciprocal interaction between self-efficacy beliefs and the learning environment; Bandura, 1983).

Competency support has demonstrated the ability to increase the motivational force of harmonious passion in high school students (Ruiz-Alfonso & León, 2019). Harmonious passion leads to a motivational state that underlies the strength of the behaviour in the direction of achievement resulting in a healthy and manageable engagement in learning (Vallerand et al., 2003). Interestingly, while trait conscientiousness is often considered the key non-intellective trait predictor of academic success in adolescents (Dumfart & Neubauer, 2016), the literature suggests it comprises both heritable stable trait facets (Krueger & Johnson, 2008) and facets such as perseverance, that may be amenable to change (Duckworth et al., 2007). In their review of trait conscientiousness, Roberts et al. (2014) suggest future research should examine the relationship between trait conscientiousness and motivational forces such as SDT's basic needs or an individual's "interests and values" (p. 1325). As such, there is a need to investigate the potential for passion for mediating the relationship between competency-supportive measures and trait conscientiousness. The COVID-19 lockdown resulted in academics having to make many time-consuming changes to match assessments with new virtual platforms; thus, their ability to provide a typical level of competency support may have been reduced (McNiff & Aicher, 2017; Pelletier et al., 2002).

The reviewed literature supported all individual connections on each pathway, except that of harmonious passion and trait conscientiousness. Additionally, despite a theoretical basis, no empirical evidence demonstrated the theorised mediation effects of technology acceptance, authentic happiness, or harmonious passion. Moreover, although theorised and reviewed as distinct, the pathways are likely to be interrelated. For example, an effective zone of proximal development requires academics to have the sensitivity to calibrate learning tasks to students' current capabilities (Sivan, 1986). Academics would likely develop this sensitivity from interpersonal connectedness. Therefore, a holistic investigation of learning processes would benefit from not only an examination of these individual pathways but also an examination of an integrated model originating from relatedness.

1.4 The rationale for the present study

By accentuating the role that educational factors play in online learning, COVID-19 represents a unique research opportunity. Although a reductionist perspective taken by researchers has identified a diverse range of educational factors in the continually expanding digital domain, there is a paucity of research that acknowledges and examines the interrelated nature of these factors. SDT explains the role of basic needs of autonomy, relatedness, and competency in driving the intrinsic motivation

that results in optimal functioning. Being self-motivated for growth in this way may be analogous to a desire to learn; thus, core needs and learning theories may overlap. Indeed, it is acknowledged that the boundaries between theories of learning are blurred and overlap (Brown, 2006; Jacobson et al., 2019), yet through the propensity for a reductionist approach, educational research continues to suffer a loss of understanding in complexity, openness, and values (Elen & Clark, 2006; Wrigley, 2019). According to one of the most influential psychologists in the field of learning, research can proceed from the study of a datum that varies in a significant fashion, and there appears to be no a priori reason why a complete description of higher mental processes cannot be reached without theory (Skinner, 1950). Therefore, this study aims to develop a final model that interrelates all data to explore this holistic gap in the existing literature.

First, it was hypothesised that students who reported higher levels of basic psychological needs fulfilment would also report more engagement in educational factors that lead to academic success. Specifically, students with greater autonomy will more readily accept technology leading to increased self-regulation of learning and course grades (H_{1a}) . COVID-19's interference would reduce a student's grades by undermining their feeling of autonomy, and by creating barriers to technology acceptance leading to reduced self-regulation and course grades (H_{1b}) . Students who feel stronger relationships with academics and peers will be more authentically happy, leading to an increased sense of classroom community and course grades (H_{2a}) . COVID-19's interference would reduce a student's grades by undermining their feeling of relatedness diminishing authentic happiness, reducing their sense of classroom community and course grades (H_{2b}) . A student who perceives more competency support from academics will be more passionate about the course and better engage trait conscientiousness, both increased competency support and conscientiousness will independently increase course grades (H_{3a}) . COVID-19's interference would reduce a student's grades by undermining an academics' capacity to provide competency support, reducing a student's harmonious passion, their engagement of trait conscientiousness, and course grades (H_{3b}) . Finally, it was hypothesised that students' academic success would be predicted by the integration of the discrete linear pathways. Specifically, the integration of the three pathways would provide a better-fitting model with more interrelated effects than the linear pathways alone $(H_4).$

1.5 Participants

Ethical approval for the study was granted by the University of the Sunshine Coast Human Ethics Committee (approval number S201243). The sample size was estimated through the statistical power analysis a priori in G*Power 3.1 (Faul et al., 2007). The analysis indicated a minimum requirement of 172 participants for the detection of a small effect size (f=0.15).

Participation in the study was limited to students who were 18 years or older, recruited through a snowball approach using social media, an undergraduate student research pool, and in-class invitations by undergraduate teaching staff via the Zoom

video conference platform. The sample comprised students (N=226, 77% female) from the University of the Sunshine Coast, Queensland, Australia, and may be considered representative given the reported prevalence of females in Australian universities, ranges between 46–72% (Australian Bureau of Statistics, 2021). Ages ranged from 18 to 70 years (M=29, SD=11.25). Most students reported their method of study as full-time (84%), were from the home institution's main campus (81%), and in their first year of study (54%). Additional demographic information is presented in Table 1.

1.6 Design

The study used a descriptive cross-sectional survey design. The predictor variables were autonomy, relatedness, competency, technology acceptance, authentic happiness, harmonious passion, self-regulation of learning, classroom community, trait conscientiousness, and COVID-19 study interference. The outcome variable was self-report of the expected course grade. Structural equation modelling was used to assess possible model fit. Parametric data was created by calculating the mean scores and averaging responses across items for all scales (Carifio & Perla, 2008; Norman, 2010).

Variable		Frequency	Percent
Previous online experience	Very experienced25Somewhat experienced43Experienced44Little experience72No experience42Dedicated study space57Dual-use study space93Shared study space29Study where I can46Must go elsewhere1No distractions28Low level distractions71Medium level distractions48High level of distractions75Must go elsewhere4No problems85	11.1	
	Somewhat experienced	43	19.0
	Experienced	44	19.5
	Little experience	72	31.9
	No experience	42	18.6
Physical study space	Dedicated study space	y experienced 25 newhat experienced 43 erienced 44 le experience 72 experience 72 licated study space 57 d-use study space 93 red study space 29 dy where I can 46 st go elsewhere 1 distractions 28 w level distractions 71 dium level distractions 48 h level of distractions 75 st go elsewhere 4 problems 79 dium level of problems 70 dium level of problems 50 h level of problems 11	25.2
	Dual-use study space	93	41.2
	Shared study space	29	12.8
	Study where I can	46	20.4
	Must go elsewhere	1	.4
Study distractions	Somewhat experienced43Experienced44Little experience72No experience42Dedicated study space57Dual-use study space93Shared study space29Study where I can46Must go elsewhere1No distractions28Low level distractions71Medium level distractions75Must go elsewhere4No problems85Low level of problems79Medium level of problems50High level of problems11	12.4	
	Low level distractions	71	31.4
	Medium level distractions	48	21.2
	High level of distractions	75	33.2
	Must go elsewhere	4	1.8
Internet problems	No problems 85		37.6
L.	Low level of problems	79	35.0
	Medium level of problems	50	22.1
	High level of problems	11	4.9
	Must go elsewhere	1	.4

 Table 1
 Summary of Demographic Variables of Previous Online Experience, Physical Study Space,

 Study Distractions, and Internet Problems

1.7 Measures

All scales demonstrated acceptable psychometric properties for use with university student populations. Cronbach's alphas from the present study are presented in Table 2.

1.7.1 Autonomy, relatedness, and competency

Students' perception of basic need fulfilment was measured using the 24-item Basic Needs and Frustration Scale (adult version; Chen et al., 2015). The items were rated on a 5-point Likert scale, ranging between (1) not at all true and (5) completely true. Composite scores were created by combining the need satisfaction and reversed need frustration items of each separate need. Possible scores ranged from 8 to 40. Scores \geq 24 indicate an overall positive perception of needs satisfaction. Sample (autonomy scale) items included '*I feel a sense of choice and freedom in the online learning I undertake*'. The scale is widely used as a measure of satisfaction or frustration of an individual's basic psychological needs and has demonstrated reliability and validity with internal consistency calculated for each subscale ranging from α =0.71 to 0.89 (Chen et al., 2015).

1.7.2 Technology acceptance

Students' behavioural intention to use technology was measured using the 17-item Technology Acceptance Model (Davis et al., 1989) modified to fit the specific context of online learning for university students (see Park, 2009). Items were scored on a 7-point Likert scale from (1) strongly disagree to (7) strongly agree. Possible scores ranged from 17 to 119, with higher scores indicating higher acceptance of technology use. Sample item: '*I find online learning systems easy to use*'. The scale is widely used as a measure of a student's capacity to use technology and has demonstrated reliability and validity with internal consistency for each subscale ranging from $\alpha = 0.76$ to 0.94 (Park, 2009).

1.7.3 Authentic happiness

Authentic happiness was measured using the 7-item authentic happiness scale (Sanli et al., 2019). Items were scored on a 5-point Likert scale from (1) not like me to (5) very like me. Possible scores ranged from 7 to 35, with higher scores indicating a higher level of authentic happiness. Sample Item: '*I am aware of the meaning of life*'. The scale was developed to examine the concept of authentic happiness levels of university students with an internal consistency of α =0.84 (Sanli et al., 2019).

1.7.4 Harmonious passion

Harmonious passion was measured using the eight-item Passion Scale (Sigmundsson et al., 2020). Items were scored on a 5-point Likert scale from (1) not like me to

Table 2 Means, Standard Deviations, Zero-Order Correlations for all Scales, Age, Biological, Sex, Grades, and Cronbach's Alpha	viations,	Zero-Orde	r Correlati	ons for all	Scales, A£	ge, Biologi	cal, Sex, (Grades, an	d Cronbac	h's Alpha					
Variable	Μ	(SD)	-	2	3	4	5	6	7	8	6	10	11	122	13
Autonomy	23.72	(5.81)	(.78)												
Relatedness	24.18	(6.39)	.61**	(.84)											
Competency	23.37	(8.69)	.75**	.62**	(.93)										
Technology Acceptance	71.19	(21.50)	.72**	.50**	.78**	(.94)									
Authentic Happiness	26.21	(4.60)	$.18^{**}$.28**	.27**	.20**	(.72)								
Harmonious Passion	29.11	6.65)	.42**	.40"	.51**	.53**	.43**	(.87)							
Self-Regulation of Learning	70.19	(12.92)	.45**	.44**	.61**	.52**	.42**	.68**	(67.)						
Classroom Community	55.65	(13.92)	**69.	.78**	.73**	.65**	.30**	.42**	.51**	(.92)					
Trait Conscientiousness	35.43	(6.78)	.12	.13*	$.16^{*}$.16*	.36**	.49**	.44**	.11	(.86)				
CO\TD-19's Interference	10.33	(2.74)	43**	33**	55**	52**	15*	34**	43**	39**	08				
Age	29	(11.52)	.07	.07	.21**	.17*	.15*	.21**	.25**	.14*	.19**	17*			
Biological Sex	NA	(NA)	.04	.02	07	.02	.11	60.	.01	.05	.02	22**	.05		
Grades COVID-19	5.91^{*}	(2.02)	.32**	.27**	.55**	.41**	.24**	.44*	.53**	.33**	.41**	37**	.22**	01	
Grades Degree	7.22 ^b	(1.52)	.08	.10	.25**	.10	60.	.25**	.36**	60.	.34**	26**	.15*	-1.0	.64
N = 226. NA = Not Applicable	le														
$^{a}5 91 \equiv a \text{ orade of } 70\%$															

 b 7.22 = a grade of 76%. Biological Sex, Male = 1, Female = 2. Cronbach's Alphas from the present study are presented in brackets. *p < .05; **p < .01; ***p < .001. $^{a}5.91 = a$ grade of 70%

(5) very like me. Possible scores ranged from 8 to 40 with higher scores indicating a higher level of harmonious passion. Sample Item: '*I have passion enough to become very good in the content of the online course*'. The scale was developed to examine the concept of engagement in valued activities and is a reliable and valid scale to ascertain the passion levels of university students with an internal consistency of $\alpha = 0.86$ (Sigmundsson et al., 2020).

1.7.5 Self-regulation of learning

Students use of learning strategies was measured by a 16-item adapted version (see Johnson & Cooke, 2016) of the Motivated Strategies for Learning Questionnaire (Pintrich, 1991). Items were scored on a 7-point Likert scale from (1) not at all true of me to (5) very true of me. Possible scores ranged from 16 to 112 with higher scores indicating a higher level of self-regulation of learning. Sample Item: '*When reading for the online courses, I make up questions to help focus my reading*'. The MSLQ has been widely used to assess the self-regulation of learning in students (Credé & Phillips, 2011) and has demonstrated reliability and validity with internal consistency for each subscale ranging from $\alpha = 0.59$ to 0.91 (Johnson & Cooke, 2016).

1.7.6 Classroom community

Classroom community was measured by the 20-item classroom community scale (Rovai, 2002). Items were scored on a 5-point Likert scale from (1) strongly disagree to (5) strongly agree. Possible scores ranged from 20 to 100 with higher scores indicating a greater sense of community. Sample item: '*I do not feel a spirit of community in the online course*'. The scale was developed to examine the concept of community in a learning environment and is a reliable and valid scale to ascertain the classroom community levels of university students with internal consistency for the subscale of connectedness, $\alpha = 0.92$ and learning $\alpha = 0.87$ (Rovai, 2002).

1.7.7 Conscientiousness

Trait conscientiousness was measured by the 10-item subscale of conscientiousness from the NEO-PI-R (Costa & McCrae, 2008). Items were scored on a 5-point Likert scale from (1) strongly disagree to (5) strongly agree. Possible scores ranged from 10 to 50, with higher scores indicating a higher level of trait conscientiousness. Sample item: '*Make plans and stick to them*'. The NEO-PI-R scale is widely used as a measure of personality traits and has demonstrated reliability and validity with internal consistency for the subscale of conscientiousness, $\alpha = 0.91$ (Costa & McCrae, 2008).

1.7.8 COVID-19 study interference

The possible challenges resulting from pandemic restrictions were constructed by combining four questions that were designed to meet the requirement of unidimensionality (Sijtsma, 2009) in assessing the impact of COVID-19. They included previous online experience, physical study space, study distractions, and internet problems that a student experienced during pandemic restrictions. The individual questions were scored on a 5-point Likert scale. For example, (1) I can study without distractions (5) There are too many distractions to study at home. Possible scores ranged from 4 to 20, with higher scores indicating a higher level of interference. Sample item: 'Select the statement that best represents the current amount of distractions that impact your study activities where you live during the COVID-19 pandemic?'.

1.7.9 Students' expectations of their future grades

Grades were predicted via self-efficacy of performance (Zimmerman & Bandura, 1994). The items were 'Select the highest grade that you feel you are most certain you could attain overall at the graduation of your degree?' and 'Select the highest grade that you feel you are most certain you could attain in your remaining online courses during the COVID-19 pandemic'. Expectancies were indicated via grade outcome percentages (50% or lower to 85% or higher). The results were converted into a scale resulting in a score reflecting the grade percentage level an individual feels capable of achieving for their degree overall and for courses completed during pandemic restrictions. A student's expectation of their future grades was found to be the most precise of 50 typical predictors of grades in a meta-analysis of educational research (Richardson et al., 2012).

1.8 Procedure

The survey was available to be completed in the final three weeks of the 12-week semester that ran from February 2020 to June 2020. The home institution ceased face-to-face education on the 23rd of March after approximately 3 weeks of study. Thus, students had completed a minimum of 6 weeks of online study. Participants responded to advertisements that included a link to the online questionnaire via Qualtrics (https://www.qualtrics.com/au/). Participants were informed that the aim of the study was to investigate university students' experience of the move to online curriculum delivery in response to enforceable physical distancing during the COVID-19 pandemic. Prior to commencement, informed consent was actively obtained via tick-box. Participants were subsequently provided with the question-naires which took an average of 25 min to complete.

1.9 Statistical analyses

The model design of the three pathways was based on the reviewed literature, with analysis following suggestions by Kline (2011) to use parcels, "a total score across a set of homogeneous items each with a Likert-type scale. Parcels are generally treated as continuous variables" (p. 179). Results were considered significant at p < 0.05. Statistical Package for the Social Sciences (SPSS Version 26.0; IBM Corp,

2017) program was used for all statistical analyses; structural equation modelling was conducted using IBM; Amos 26.0. in SPSS. Model fit was regarded as acceptable if: the Normed Fit Index (NFI) \geq 0.90 (Byrne, 1994) or 0.95 (Schumacker & Lomax, 2004); the Tucker Lewis index (TFI) \geq 0.90 (Hoyle, 1995); the Comparative Fit Index (CFI) \geq 0.93 (Byrne, 1994); RMSEA \leq 0.08 (Browne & Crudeck, 1993) and ideally \leq 0.05 (Steiger, 1990); the relative chi-square (χ^2/df) is \leq 2 (Kline, 2011; Tabachnick et al., 2007). AIC is a fit measure relative to the value of the saturated model; good fit occurs when the AIC is less than the saturated model (Burnham & Anderson, 1998).

2 Results

2.1 Preliminary analysis

Mean scores, standard deviations, and zero-order correlations between study variables are presented in Table 2. Students who perceived greater psychological need fulfilment of autonomy, relatedness, and competency reported significantly higher levels of technology acceptance, authentic happiness, harmonious passion, self-regulation of learning, classroom community, trait conscientiousness and grades. The four COVID-19 interference questions shared small positive correlations (r=.10 to .22) and were all negatively correlated with the outcome measure of expected academic grades (r=-.17 to -.22).

2.2 Assumptions

Of the original 328 survey responses, 99 cases were removed due to missing data. An analysis of standardised values of all variables revealed one univariate outlier fell outside the cut off (Maximum, Z > 3.29, Minimum, Z < -3.29) which was removed. Multivariate outliers were assessed via Mahalanobis distance and interpreted via a χ^2 distribution, with degrees of freedom equivalent to the number of independent variables in the regression (Tabachnick et al., 2007). Two multivariate outliers were removed due to a violation of the critical χ^2 value ($\alpha = 0.001$) of the structural models. Cook's distance was below 0.85 for all cases (Cook & Weisberg, 1982). Considering the final sample (N=226) in the context of the central limit theory (Wilcox, 2010), the assumptions of normality for means-testing, and sample size for structural equation modelling were met (Field, 2018; Kline, 2011).

2.3 Main analysis

2.3.1 COVID-19's impact on grades

The incorporation of a self-report strategy allowed the overall impact of COVID-19 on a student's grades to be estimated via a paired sample *t*-test. The result from the questions '*estimate what you believe your overall degree grade will be when you*

174

finish all courses' (M=7.22, SD=1.52) and 'estimate what you expect to receive as a grade in the online courses during the COVID 19 pandemic' (M=5.91, SD=2.02) demonstrate that the presence of pandemic restrictions resulted in a statistically significant expected reduction, on average, of 6% of a student's grade, t(225)=12.50, p < .001, d=0.73.

2.3.2 Group differences

A series of one-way between-groups ANOVA revealed no significant differences between the groups of method of study, campus, or year of study on the variables of COVID-19 interference or grades. However, differences were apparent based on age (i.e., comparing students under and over 25 years) and gender. First, older students (46%) reported less COVID-19 interference (M=9.93, SD=2.88) than younger students (M=10.67, SD=2.58), t(224)=2.04, p=.042, g=0.30. Second, older students expected higher grades (M=6.39, SD=1.98) than younger students (M=5.51, SD=1.98), t(224)=-3.32, p=.001, g=0.44. Third, women (M=10.67, SD=2.65), t(224)=-3.39, p=.001, g=0.54. Specifically, for women (M=2.97, SD=1.07) study distraction caused by family or others in the home was significantly higher compared to men (M=2.25, SD=0.97), t(224)=-4.367, p<.001, g=0.69.

2.3.3 Structural equation modelling

2.4 Autonomy

The first model to be tested was the hypothesised autonomy pathway, as shown in Fig. 1, which was supported by all hypothesised connections being significant as shown in Fig. 4. The fit of the model was excellent, $\chi^2/df = 1.587$ ($\chi^2 = 15.87$, 10 *df*), p = 0.104; CFI=0.986, NFI=0.965, TLI=0.971, RMSEA=0.051 (95% CI=0.000-0.096), AIC=51.87 (AIC saturated 56.00).

2.5 Relatedness

The model for the relatedness pathway (as shown in Fig. 2) was not supported by the data. After removing the non-significant hypothesised pathways (COVID-19 Interference \rightarrow Authentic Happiness and Authentic happiness \rightarrow Classroom Community) as suggested by (Kline, 2011), the modification indices indicated the inclusion of a direct path from COVID-19 interference to grades. This modified model was supported by the data (as shown in Fig. 5 and had an excellent fit), $\chi^2/df=1.360$ ($\chi^2=13.60$, 10 *df*), p=0.192; CFI=0.989, NFI=0.962, TLI=0.977, RMSEA=0.040 (95% CI=0.000-0.088), AIC=49.60 (AIC saturated 56.00).

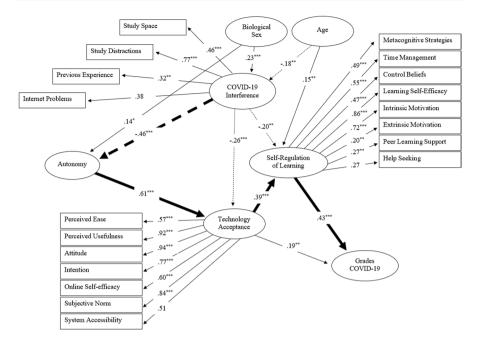


Fig. 4 The Autonomy Pathway Model. *Note* Beta coefficients greater than $\beta = \pm .3$ are presented in bold lines and negative beta coefficients are presented as dashed lines. Biological sex, 1=male, 2=female. (Standardised solution; N = 226). *p < .05; **p < .01; ***p < .001

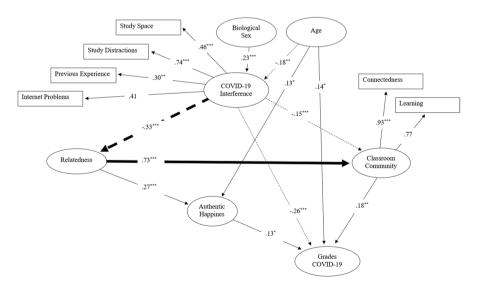


Fig. 5 The Relatedness Pathway Model. *Note* Beta coefficients greater than $\beta = \pm .3$ are presented in bold lines and negative beta coefficients are presented as dashed lines. Biological sex, 1 = male, 2 = female. (Standardised solution; N=226). *p < .05; **p < .01; ***p < .001

🙆 Springer

2.6 Competency

The model for the competency pathway as shown in Fig. 3 was supported by the data, although three connections were non-significant. After removing the non-significant pathways (COVID-19 Interference \rightarrow Harmonious Passion, COVID-19 \rightarrow Conscientiousness, and Passion \rightarrow Grades), the final model, as shown in Fig. 6, had excellent fit, $\chi^2/df=1.600$ ($\chi^2=19.20$, 12 *df*), p=.084; CFI=0.980, NFI=0.949, TLI=0.964, RMSEA=0.052 (95% CI=0.000-0.093), AIC=51.20 (AIC saturated 56.00).

2.7 Integrated model

The final model to be tested was the combination of the three previous models; however, this did not have a good fit. The integrated model was improved by removing the non-significant pathways, and by using the modification indices in several steps in line with the reviewed literature to ensure changes were theoretically sound, the final model is shown in Fig. 7. The integrated model had very good fit, $\chi^2/df = 1.476$ ($\chi^2 = 72.32$, 49 *df*), p = .017; CFI=0.984, NFI=0.953, TLI=0.975, RMSEA=0.046 (95% CI=0.024-0.067), AIC=156.32 (AIC saturated=182.00).

The results suggest that 44% of the variance in students' expectations of their future grades during COVID-19 restrictions is explained by the determinants of the

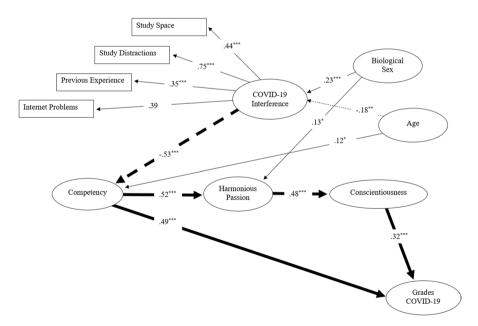


Fig. 6 The Competency Pathway Model. *Note* Beta coefficients greater than $\beta = \pm .3$ are presented in bold lines and negative beta coefficients are presented as dashed lines. Biological sex, 1 =male, 2 =female. (Standardised solution; N = 226). *p < .05; **p < .01; ***p < .001

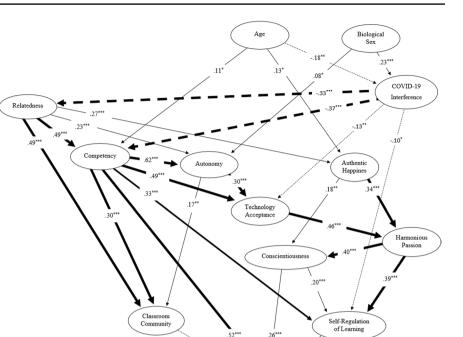


Fig. 7 The Integrated Pathway Model. *Note* Beta coefficients greater than $\beta = \pm .3$ are presented in bold, and negative beta coefficients are presented as dashed lines. Biological Sex, 1 = male, 2 = female. (Standardised solution; N = 226). *p < .05; **p < .01; ***p < .001

- 17

10

Grades COVID-19

integrated model. Squared multiple correlations (R^2) represent the proportion of total variance on a variable that is accounted for by the predictors and are presented in Table 3.

3 Discussion

The present study aimed to assess the role of three core psychological needs in the process of learning, specifically in the online learning environment and, even more specifically, under conditions that forced students into this mode of learning due to COVID-19 restrictions. These three learning pathways, each originating with one of SDT's well-known basic psychological needs and integrating educational factors were aligned by fundamental theories of learning. The proposed pathways were then used to empirically test the relationship between psychological needs and educational factors to investigate how these determinates could explain course grades during the impact of COVID-19 and beyond. The results of the individual pathway structural models support the hypotheses that relationships exist between the

Predictors	Standardised beta coefficients effects on grades					
	$\overline{R^2}$	Direct	Indirect	Total	Order of contri- bution to grades	
COVID-19 interference	(.09)	_	314	314	12	
Autonomy	(.60)	-	003	003	9	
Relatedness	(.11)	-	.225	.225	3	
Competency	(.52)	.521***	.050	.572	1	
Technology acceptance	(.66)	-	.088	.088	8	
Authentic happiness	(.09)	-	.119	.119	7	
Harmonious passion	(.38)	-	.190	.190	4	
Self-regulation of learning	(.58)	.183**	-	.183	5	
Classroom community	(.72)	171*	-	171	11	
Conscientiousness	(.26)	.258***	.037	.294	2	
Age		-	.137	.137	6	
Biological sex		-	073	073	10	

 Table 3
 Squared Multiple correlations, Standardised Direct, Indirect, and Total Effects for the Predictor

 Variables, COVID-19
 Interference, Basic Psychological Needs, and Educational Factors on Grades for

 the Integrated Structural Model
 Integrated Structural Model

N=226. Order of contribution to grades, 1= largest contributor to grades, 12= largest hindrance to grades. p < .05; **p < .01; ***p < .001

concept of specific need fulfilment and pathways of educational factors (H_{1a} , H_{2a} , and H_{3a}). The results of the integrated pathway model provided supporting evidence of a more complex interrelationship between a student's basic psychological needs and the educational factors that typically predict course grades (H_4). COVID-19's negative relationship to expected grades was larger than trait conscientiousness's positive relationship, COVID-19 primarily impacted the social and more vulnerable state type factors (partially supporting, H_{1b} , H_{2b} , and H_{3b}). This pattern of results is consistent with the evidence from preliminary COVID-19 research in which students repeatedly identified a lack of social interaction and a lack of appropriate skills as barriers to online learning (Aboagye et al., 2020; Anwar et al., 2020). Our findings highlight that students who perceive their learning environment to fulfil their basic psychological needs may be more likely to be inspired to proactively engage in a wide range of educational factors that enhance the processes of learning.

3.1 Discrete pathways

The results of the three discrete pathways supported the hypothesised links between each of the individual psychological needs and educational factors, except for the proposed mediation effect of authentic happiness. This pattern of results is consistent with the large volume of educational research previously reviewed. However, the purpose of this study was to gain a holistic understanding of the interrelated complexity of these educational factors within the expanding digital domain. To this end, the integrated structural model fit superseded the discrete pathways enabling a real-world interpretation of educational data (Wrigley, 2019).

3.2 Integration of the discrete linear pathways

The integrated model provided empirical evidence of eight additional non-hypothesised mediating relationships and was consistent with the presupposition that all learning begins with relatedness (Trespalacios & Uribe-Florez, 2020; Van Fleet, 1979). Relatedness strongly predicted competency and mildly predicted autonomy. However, whereas previous research found competency to directly predict both harmonious passion and trait conscientiousness (Ruiz-Alfonso & León, 2019; Trautwein et al., 2009), the present study has shown these relationships may be mediated by autonomy and technology acceptance. Competency demonstrated the most considerable relationship with grades, providing empirical support for the benefit of reciprocal determinism (Bandura, 1983). This idea is further supported by the findings that demonstrate this phenomenon occurs cross-culturally (Williams & Williams, 2010) and in both adults and children (Talsma et al., 2018).

In the integrated model, autonomy did not predict academic success, possibly because of a suppressor effect. A suppressor is defined as a third variable that increases or decreases the regression coefficient between the predictor and outcome variable by its inclusion in a regression equation (Conger, 1974). Feasibly, the relationship between autonomy and grades has been suppressed by the classroom community, which also predicted a negative effect on grades. Indeed, the overall suppression of both variables may be linked to the construct overlap (multicollinearity) between relatedness and classroom community (Ho, 2006), in which one predictor variable is utilising redundant information leading to unstable regression coefficient estimates (Raykov & Marcoulides, 2012). Therefore, a possibility exists that overlapping questions between the relatedness scale and classroom community subscale of connectedness subsumed the classroom community's positive relationship, which, in turn, suppressed autonomy. Thus, the direct regression coefficient between classroom community and grades should be treated with caution, particularly as both autonomy and classroom community displayed positive correlations with grades. However, despite of a suppression effect, these results are consistent with Boydie (2020), who found no relationship between a classroom community and grades, and Beachboard et al.'s (2011) work that indicated relatedness to academics is more consequential to grades than a sense of community.

Continuing, the integrated model revealed that authentic happiness predicted harmonious passion and trait conscientiousness. Part of being authentically happy is congruence between desires and actions (Seligman & Csikszentmihalyi, 2000); therefore, the connection between authentic happiness and harmonious passion is logical. However, the logic behind the association between authentic happiness and trait conscientiousness is not clear. The most compelling explanation for the current set of findings is that being authentically happy provides emotional resilience to the impact of phenomena such as COVID-19, a concept supported in the literature (Seligman et al., 2009; Yildirim & Belen, 2018) and aligns with

research examining neural imaging that indicates emotional distractions disrupt the neural circuitry involved in goal-directed processing (Blair et al., 2007).

Interestingly, in the reviewed research, Nikou and Economides (2017) found that autonomy strongly predicted technology acceptance, while Fathali and Okada (2018) found it was moderately predicted by competency. The integrated results were consistent with both studies but aligned more strongly with Fathali and Okada (2018). Moreover, whereas past researchers (Liaw & Huang, 2013) found that technology acceptance predicted self-regulation of learning, the integrated model revealed harmonious passion may mediate this relationship. Findings reduce the paucity of educational literature surrounding harmonious passion (Ruiz-Alfonso & León, 2016, 2019) by demonstrating the possibility that harmonious passion may be a resilient motivational force that can predict students' engagement of trait conscientiousness and self-regulation of learning. Evidence that harmonious passion predicts trait conscientiousness may be explained by the notion that trait conscientiousness may be stimulated by state-type factors (e.g., perseverance; Duckworth et al., 2007).

Consistent with the robust evidence supporting the influence of trait conscientiousness (e.g., Alkış & Temizel, 2018; Sorić et al., 2017; Trapmann et al., 2007; Vedel, 2014) the results of the present study revealed a strong relationship with expected grades. Greater conscientiousness also predicted self-regulation of learning. Indeed, all paths led to self-regulation of learning; out of eight educational factors, four indirectly and three directly predicted self-regulation of learning. The present results are consistent with research demonstrating that the digital domain necessitates higher levels of self-regulation than traditional classroom settings (Inan et al., 2017; Onah & Sinclair, 2017; Wandler & Imbriale, 2017). This finding may be explained by the idea that self-regulation of learning is a vital factor in psychological constructivism, optimally transforming new information into personal knowledge.

Age was a protective factor against COVID-19's interference and positively predicted authentic happiness and competency. These results are consistent with the claims that authentic happiness increases with age (Tanzer, 2019) and that being older increases self-efficacy beliefs (Huang, 2013). Therefore, younger individuals may have experienced higher levels of negative affect and perhaps a less concrete self-concept, which would explain their significantly lower expected course grades. So too, females experienced significantly higher levels of COVID-19 interference than males, specifically, distractions from others in the home. The present results are consistent with Zhao et al.'s (2019) work that deals with the negative effect that gender role orientation may have in the workplace. However, in contrast to the effect of age, no sex difference was found in expected grades. This anomaly may be explained by females reporting higher levels of autonomy, and harmonious passion, which was also apparent in autonomous language learning (Varol & Yilmaz, 2010). The present study provides evidence to support the notion that females are more intrinsically motivated and passionate, resulting in a state of optimal functioning that is more resilient than males, which counterbalanced COVID-19's impact.

3.3 Real-world implications

The integrated results support the long-held view that the transmission of information hinges on inherent respect and trust between learner and academic (Van Fleet, 1979). This effect has been demonstrated more recently in first-year undergraduate students. In their study, Ambikairajah et al. (2019) found that brief 2-min conversations between academics and students significantly improved student perception of academic support. The integrated model extends the educational literature by demonstrating new mechanisms through which these positive relationships could foster learning throughout the complex pathways. For example, in the current study, relatedness directly predicted a student's authentic happiness which, in turn, predicted educational factors not typically associated with social interaction, such as trait conscientiousness. The results also strongly imply that authentic happiness plays an important role in the processes of learning and supports the current trend of incorporating positive psychology into education (Dewaele et al., 2019; Norrish et al., 2013; Trask-Kerr et al., 2019). The finding that technology acceptance predicted harmonious passion was unexpected and demonstrated a unique motivational pathway. One interpretation of these findings is that as students use technology to acquire new information, it is a passion for the topic of study that increases the conscientious motivation to self-regulate learning. Thus, academics that are connected with their students and provide interesting and topical learning material are likely to inspire an autonomous and competent use of technology to increase passion and the conscientious use of strategies to construct personal knowledge.

The integrated results confirmed the stalwarts of educational research, that is, competency beliefs, trait conscientiousness, and self-regulation of learning were direct predictors of expectations of grades. Educational research supports the involvement of competency-beliefs in Bandura's (1983) reciprocal determinism (Talsma et al., 2018; Williams & Williams, 2010). The integrated results indicate that this bidirectional self-influence predicts academic grades at a magnitude double that of trait conscientiousness. Therefore, academics providing competency support can feel a renewed faith in the efficacy of the zone of proximal development as an educational tool in the expanding digital domain. Finally, it may be time to re-examine the preconceived notion that conscientiousness is a stable trait factor. Consistent with Eisenberg et al.'s (2014) work that demonstrated self-regulation skills to be a core component in the development of more trait conscientiousness, the integrated model revealed harmonious passion might be the key to unlocking a student's full conscientious potential. In sum, considering the discussed interrelationships, to assist students during COVID-19 and beyond, it is an academic's relatedness to their students that may be the most influential factor in a student's academic success.

3.4 Limitations and future research directions

Although strong theoretical support for the identified relationships, it is important to understand that model fit represents possibility and not causality. The

self-report data this study relied upon may be vulnerable to common-method bias. Also, some students may have chosen to withdraw from studies during the pandemic, which may have resulted in a sample of determined students, or equally, a sample of students that had no other choice. The predictor variable COVID-19's interference was based upon quantifiable physical environmental factors and is not a measure of negative affect or reduced wellbeing, which may range widely with an individual's level of resilience and coping strategies. Although meeting the assumptions of multicollinearity (VIF less than 5; Becker et al., 2015), the use of the predictor variable of classroom community was questionable. The overlap between relatedness questions, such as 'I feel connected with the people in the online courses who care for me, and for whom I care' and classroom community questions, such as 'I feel connected to others in the online courses' should have been detected a priori to the investigation. A future research consideration may be that any effect from the development of a classroom community, like that of relatedness, is likely disseminated at the beginning of learning pathways. The strongest effect on grades can be explained by the theory of reciprocal determinism. Bandura (1983) points out that behaviour is regulated by the afterword contingency of an individual's own actions, and this contingency is mutually derived from cognition, behaviour, and the environment. Future studies might adopt a longitudinal approach exploring students' cognitions, behaviours, and learning environments with actual records of academic grades over time to ascertain educational factors and practices that may better create this state of positive and reciprocal self-influence. Despite these limitations, the current study uniquely contributes to the educational literature by providing a relatively comprehensive and theoretically driven model to explain how academics can enhance learning processes in the expanding digital domain.

4 Conclusion

Although COVID-19 is novel, there will always be change. Thus, research needs to determine proper ways to enhance students learning and inform pedagogical designs. The findings of this study have implications for academics working in the expanding digital domain by demonstrating the interrelated complexity between academic support of the core needs and educational factors in the processes of online student-centred learning. When academics implement supportive measures that fulfil a student's psychological needs, it results in students being propelled by a feeling of relatedness, becoming more autonomous and self-efficacious, thus, optimally functioning, and proactively engaging in a wide range of educational factors that follow complex, interrelated pathways to academic success.

Acknowledgements Nil

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval Ethical approval for this project was obtained from the University of the Sunshine Coast Ethics Committee, approval number: S201243.

References

- Aboagye, E., Yawson, J. A., & Appiah, K. N. (2021). COVID-19 and e-learning: The challenges of students in tertiary institutions. Social Education Research, 2(1), 1–8. https://doi.org/10.37256/ser. 122020422
- Aithal, P. S., & Aithal, S. (2019). Building world-class universities: Some insights & predictions. International Journal of Management, Technology, and Social Sciences (IJMTS), 4(2), 13–35.
- Alkış, N., & Temizel, T. T. (2018). The impact of motivation and personality on academic performance in online and blended learning environments. *Journal of Educational Technology and Society*, 21(3), 35–47.
- Ambikairajah, A., Ambikairajah, R., & Ambikairajah, E. (2021). The impact of improving feelings of relatedness on motivation and engagement for tertiary students. *International Journal of Mathematical Education in Science and Technology*, 52(5), 721–730. https://doi.org/10.1080/0020739X. 2019.1703149
- Anwar, M., Khan, A., & Sultan, K. (2020). The barriers and challenges faced by students in online education during COVID-19 pandemic in Pakistan. *Gomal University Journal of Research*, 36(1), 52–62.
- Australian Bureau of Statistics. (2021). Education and Work, Australia. https://www.abs.gov.au/statistics/ people/education/education-and-work-australia/latest-release
- Bandura, A. (1977). Social learning theory. Prentice Hall.
- Bandura, A. (1983). Temporal dynamics and decomposition of reciprocal determinism: A reply to Phillips and Orton. *Psychological Review*, 90(2), 166–170. https://doi.org/10.1037/0033-295X.90.2. 166
- Beachboard, M. R., Beachboard, J. C., Li, W., & Adkison, S. R. (2011). Cohorts and relatedness: Selfdetermination theory as an explanation of how learning communities affect educational outcomes. *Research in Higher Education*, 52(8), 853–874. https://doi.org/10.1007/s11162-011-9221-8
- Becker, J. M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing Letters*, 26(4), 643–659. https://doi.org/10.1007/s11002-014-9299-9
- Blair, K. S., Smith, B. W., Mitchell, D. G. V., Morton, J., Vythilingam, M., Pessoa, L., Fridberg, D., Zametkin, A., Nelson, E. E., Drevets, W. C., Pine, D. S., Martin, A., & Blair, R. J. R. (2007). Modulation of emotion by cognition and cognition by emotion. *NeuroImage*, 35(1), 430–440. https:// doi.org/10.1016/j.neuroimage.2006.11.048
- Booker, K. (2008). The role of instructors and peers in establishing classroom community. *Journal of Instructional Psychology*, 35(1), 12–16.
- Booker, K. (2016). Connection and commitment: How sense of belonging and classroom community influence degree persistence for African American undergraduate women. *International Journal of Teaching and Learning in Higher Education*, 28(2), 218–229.
- Boydie, M. R. (2020). Predicting academic achievement based on sense of community among online public high school students (Publication Number 2429) [Doctoral dissertation, Liberty University]. https://digitalcommons.liberty.edu/doctoral/2429
- Broadbent, J., & Fuller-Tyszkiewicz, M. (2018). Profiles in self-regulated learning and their correlates for online and blended learning students. *Educational Technology Research and Development*, 66(6), 1435–1455. https://doi.org/10.1007/s11423-018-9595-9
- Bronfenbrenner, U. (1979). The ecology of human development: Experiments by nature and design. Harvard University Press.
- Bronfenbrenner, U., & Ceci, S. J. (1994). Nature-nurture reconceptualised in developmental perspective: A bioecological model. *Psychological Review*, 101(4), 568–586. https://doi.org/10.1037/0033-295X.101.4.568
- Brown, T. H. (2006). Beyond constructivism: Navigationism in the knowledge era. On the Horizon, 14(3), 108–120. https://doi.org/10.1108/10748120610690681
- Browne, M., & Crudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162). Sage.

- Burnham, K. P., & Anderson, D. R. (1998). Practical use of the information-theoretic approach. In K. P. Burnham & D. R. Anderson (Eds.), *Model selection and inference* (pp. 75–117). Springer New York. https://doi.org/10.1007/978-1-4757-2917-7_3
- Byrne, B. M. (1994). Structural equation modeling with EQS and EQS/Windows: Basic concepts, applications, and programming. Sage.
- Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J., & Zheng, J. (2020). The psychological impact of the COVID-19 epidemic on college students in China. *Psychiatry Research*, 287, 1–5. https:// doi.org/10.1016/j.psychres.2020.112934
- Carifio, J., & Perla, R. (2008). Resolving the 50-year debate around using and misusing Likert scales. Medical Education, 42(12), 1150–1152. https://doi.org/10.1111/j.1365-2923.2008.03172.x
- Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E., Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R., Sheldon, K., Soenens, B., Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion*, 39(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1
- Chen, K. C., & Jang, S. J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior*, 26(4), 741–752. https://doi.org/10.1016/j.chb.2010. 01.011
- Conger, A. J. (1974). A revised definition for suppressor variables: A guide to their identification and interpretation. *Educational and Psychological Measurement*, 34(1), 35–46. https://doi.org/10. 1177/001316447403400105
- Conti, G., & Heckman, J. J. (2014). Understanding conscientiousness across the life course: An economic perspective. *Developmental Psychology*, 50(5), 1451–1459. https://doi.org/10.1037/ a0036426
- Cook, R. D., & Weisberg, S. (1982). Residuals and influence in regression. Chapman & Hall.
- Costa, P. T., & McCrae, R. R. (1992). *Neo personality inventory-revised (NEO PI-R)*. Psychological Assessment Resources.
- Costa, P. T., & McCrae, R. R. (2008). The NEO Inventories. In R. P. Archer & S. R. Smith (Eds.), Personality assessment (pp. 213–245). Routledge.
- Credé, M., & Phillips, L. A. (2011). A meta-analytic review of the motivated strategies for learning questionnaire. *Learning and Individual Differences*, 21(4), 337–346. https://doi.org/10.1016/j.lindif. 2011.03.002
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003. https://doi.org/10.1287/ mnsc.35.8.982
- Deci, E. L., & Ryan, R. M. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. https://doi.org/10.1037/ 0003-066X.55.1.68
- Department of Health. (2020). Coronavirus (COVID-19) restrictions. https://www.health.gov.au/news/ health-alerts/novel-coronavirus-2019-ncov-health-alert/coronavirus-covid-19-restrictions
- Dewaele, J. M., Chen, X., Padilla, A. M., & Lake, J. (2019). The flowering of positive psychology in foreign language teaching and acquisition research. *Frontiers in Psychology*, 10, 1–13. https://doi.org/ 10.3389/fpsyg.2019.02128
- Dickinson, L. (1995). Autonomy and motivation a literature review. *System*, 23(2), 165–174. https://doi. org/10.1016/0346-251X(95)00005-5
- Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, 92(6), 1087–1101. https://doi. org/10.1037/0022-3514.92.6.1087
- Dumfart, B., & Neubauer, A. C. (2016). Conscientiousness is the most powerful noncognitive predictor of school achievement in adolescents. *Journal of Individual Differences*, 37(1), 8–15. https://doi. org/10.1027/1614-0001/a000182
- Dunn, J. R., & Schweitzer, M. E. (2005). Feeling and believing: The influence of emotion on trust. *Journal of Personality and Social Psychology*, 88(5), 736–748. https://doi.org/10.1037/0022-3514.88.5. 736
- Dziuban, C., Graham, C. R., Moskal, P. D., Norberg, A., & Sicilia, N. (2018). Blended learning: The new normal and emerging technologies. *International Journal of Educational Technology in Higher Education*, 15(1), 1–16. https://doi.org/10.1186/s41239-017-0087-5
- Eisenberg, N., Duckworth, A. L., Spinrad, T. L., & Valiente, C. (2014). Conscientiousness: Origins in childhood? *Developmental Psychology*, 50(5), 1331. https://doi.org/10.1037/a0030977

- Elen, J., & Clark, R. E. (2006). Handling complexity in learning environments: Theory and research. Emerald Group Publishing.
- Fathali, S., & Okada, T. (2018). Technology acceptance model in technology-enhanced OCLL contexts: A self-determination theory approach. *Australasian Journal of Educational Technology*, 34(4), 138–154. https://doi.org/10.14742/ajet.3629
- Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191. https://doi.org/10.3758/BF03193146
- Field, A. (2018). Discovering statistics using IBM SPSS statistics (5th ed.). Sage Publications.
- Gilal, F. G., Channa, N. A., Gilal, N. G., Gilal, R. G., & Shah, S. M. M. (2019). Association between a teacher's work passion and a student's work passion: A moderated mediation model. *Psychology Research and Behavior Management*, 12, 889–900. https://doi.org/10.2147/PRBM.S212004
- Ho, R. (2006). Handbook of univariate and multivariate data analysis and interpretation with SPSS. CRC Press.
- Hoyle, R. H. (1995). Structural equation modeling: Concepts, issues, and applications. Sage.
- Huang, C. (2013). Gender differences in academic self-efficacy: A meta-analysis. European Journal of Psychology of Education, 28(1), 1–35. https://doi.org/10.1007/s10212-011-0097-y
- Illeris, K. (2007). How we learn: Learning and non-learning in school and beyond. Routledge.
- Illeris, K. (2018). Contemporary theories of learning: Learning theorists... in their own words. Routledge.
- IBM Corp. (2017). IBM SPSS Statistics for Windows. In (Version 25.0) IBM Corp.
- Inan, F., Yukselturk, E., Kurucay, M., & Flores, R. (2017). The impact of self-regulation strategies on student success and satisfaction in an online course. *International Journal on E-Learning*, 16(1), 23–32.
- Jacobson, M. J., Levin, J. A., & Kapur, M. (2019). Education as a complex system: Conceptual and methodological implications. *Educational Researcher*, 48(2), 112–119. https://doi.org/10.3102/00131 89X19826958
- Johnson, G. M., & Cooke, A. (2016). Self-regulation of learning and preference for written versus audiorecorded feedback by distance education students. *Distance Education*, 37(1), 107–120. https://doi. org/10.1080/01587919.2015.1081737
- King, R. B. (2015). Sense of relatedness boosts engagement, achievement, and well-being: A latent growth model study. *Contemporary Educational Psychology*, 42, 26–38. https://doi.org/10.1016/j. cedpsych.2015.04.002
- Kirk, G. S., Raven, J. E., & Schofield, M. (1983). The presocratic philosophers: A critical history with a selection of texts. Cambridge University Press.
- Kline, R. B. (2011). Principles and practice of structural equation modeling. Guilford.
- Krueger, R. F., & Johnson, W. (2008). Behavioral genetics and personality: A new look at the integration of nature and nurture. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 287–310). The Guilford Press.
- Liaw, S. S., & Huang, H. M. (2013). Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments. *Computers and Education*, 60(1), 14–24. https://doi.org/10.1016/j.compedu.2012.07.015
- Maslow, A. H. (1943). A theory of human motivation. Psychological Review, 50(4), 370–396. https://doi. org/10.1037/h0054346
- McNiff, J., & Aicher, T. (2017). Understanding the challenges and opportunities associated with online learning: A scaffolding theory approach. Sport Management Education Journal, 11(1), 13–23. https://doi.org/10.1123/smej.2016-0007
- Morcom, V. E., & MacCallum, J. A. (2012). Getting personal about values: Scaffolding student participation towards an inclusive classroom community. *International Journal of Inclusive Education*, 16(12), 1323–1334. https://doi.org/10.1080/13603116.2011.572189
- Nahyun, K., & Hana, S. (2017). Personality, traits, gender, and information competency among college students. *Malaysian Journal of Library and Information Science*, 16(1), 87–107.
- Niemiec, C. P., & Ryan, R. M. (2009). Autonomy, competence, and relatedness in the classroom: Applying self-determination theory to educational practice. *Theory and Research in Education*, 7(2), 133–144. https://doi.org/10.1177/1477878509104318
- Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Integrating acceptance and motivational factors into a combined model of self-determination theory and technology acceptance. *Computers in Human Behavior*, 68, 83–95. https://doi.org/10.1016/j.chb.2016.11.020

- Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. Advances in Health Sciences Education: Theory and Practice, 15, 625–632. https://doi.org/10.1007/ s10459-010-9222-y
- Norrish, J. M., Williams, P., O'Connor, M., & Robinson, J. (2013). An applied framework for positive education. *International Journal of Wellbeing*, 3(2), 147–161. https://doi.org/10.5502/ijw.v3i2.2
- Onah, D., & Sinclair, J. (2017). Assessing self-regulation of learning dimensions in a stand-alone MOOC platform. *International Journal of Engineering Pedagogy*, 7(2), 4–21. https://doi.org/10.3991/ijep. v7i2.6511
- Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Journal of Educational Technology and Society*, 12(3), 150–162.
- Pelletier, L. G., Séguin-Lévesque, C., & Legault, L. (2002). Pressure from above and pressure from below as determinants of teachers' motivation and teaching behaviors. *Journal of Educational Psychol*ogy, 94(1), 186–196. https://doi.org/10.1037/0022-0663.94.1.186
- Piaget, J. (1973). Psychology and epistemology. Grossman.
- Pintrich, P. R. (1991). A manual for the use of the motivated strategies for learning questionnaire (MSLQ). https://files.eric.ed.gov/fulltext/ED338122.pdf
- Pogorskiy, E., Beckmann, J. F., Joksimović, S., Kovanović, V., & West, R. (2018). Utilising a virtual learning assistant as a measurement and intervention tool for self-regulation in learning. In 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE) (pp. 846–849). https://doi.org/10.1109/TALE.2018.8615130
- Raykov, T., & Marcoulides, G. A. (2012). A first course in structural equation modeling. Routledge.
- Reeve, J., Jang, H., Carrell, D., Jeon, S., & Barch, J. (2004). Enhancing students' engagement by increasing teachers' autonomy support. *Motivation and Emotion*, 28(2), 147–169. https://doi.org/10. 1023/B:MOEM.0000032312.95499.6f
- Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, 138(2), 353– 387. https://doi.org/10.1037/a0026838
- Roberts, B. W., Hill, P. L., & Davis, J. P. (2017). How to change conscientiousness: The sociogenomic trait intervention model. *Personality Disorders: Theory, Research, and Treatment*, 8(3), 199–205. https://doi.org/10.1037/per0000242
- Roberts, B. W., Lejuez, C., Krueger, R. F., Richards, J. M., & Hill, P. L. (2014). What is conscientiousness and how can it be assessed? *Developmental Psychology*, 50(5), 1315–1330. https://doi.org/10. 1037/a0031109
- Rocchi, M. A., Pelletier, L. G., & Lauren Couture, A. (2013). Determinants of coach motivation and autonomy-supportive coaching behaviours. *Psychology of Sport and Exercise*, 14(6), 852–859. https://doi.org/10.1016/j.psychsport.2013.07.002
- Ross, A., Talmage, C. A., & Searle, M. (2019). Toward a flourishing neighborhood: The association of happiness and sense of community. *Applied Research in Quality of Life*, 14(5), 1333–1352. https:// doi.org/10.1007/s11482-018-9656-6
- Rovai, A. P. (2001). Building classroom community at a distance: A case study. *Educational Technology Research and Development*, 49(4), 33–48. https://doi.org/10.1007/BF02504946
- Rovai, A. P. (2002). Development of an instrument to measure classroom community. *The Internet and Higher Education*, 5(3), 197–211. https://doi.org/10.1016/S1096-7516(02)00102-1
- Ruiz-Alfonso, Z., & León, J. (2016). The role of passion in education: A systematic review. *Educational Research Review*, 19, 173–188. https://doi.org/10.1016/j.edurev.2016.09.001
- Ruiz-Alfonso, Z., & León, J. (2019). Teaching quality: Relationships between passion, deep strategy to learn, and epistemic curiosity. *School Effectiveness and School Improvement*, 30(2), 212–230. https://doi.org/10.1080/09243453.2018.1562944
- Sanli, E., Celik, S. B., & Gencoglu, C. (2019). Validity and reliability of the authentic happiness scale. *Khazar Journal of Humanities and Social Science*, 22(1), 5–20. https://doi.org/10.5782/2223-2621. 2019.22.1.5
- Santini, Z. I., Jose, P. E., York Cornwell, E., Koyanagi, A., Nielsen, L., Hinrichsen, C., Meilstrup, C., Madsen, K. R., & Koushede, V. (2020). Social disconnectedness, perceived isolation, and symptoms of depression and anxiety among older Americans (NSHAP): A longitudinal mediation analysis. *The Lancet Public Health*, 5(1), 62–70. https://doi.org/10.1016/S2468-2667(19)30230-0

- Schaefer, T., Fabian, C. M., & Kopp, T. (2020). The dynamics of online learning at the workplace: Peerfacilitated social learning and the application in practice. *British Journal of Educational Technol*ogy, 51(4), 1406–1419. https://doi.org/10.1111/bjet.12894
- Schumacker, R. E., & Lomax, R. G. (2004). A beginner's guide to structural equation modeling. Psychology Press.
- Seligman, M. E. (2004). Authentic happiness: Using the new positive psychology to realise your potential for lasting fulfillment. Simon and Schuster.
- Seligman, M. E. P., & Csikszentmihalyi, M. (2000). Positive psychology. American Psychologist, 55(1), 5–14. https://doi.org/10.1037/0003-066X.55.1.5
- Seligman, M. E. P., Ernst, R. M., Gillham, J., Reivich, K., & Linkins, M. (2009). Positive education: Positive psychology and classroom interventions. Oxford Review of Education, 35(3), 293–311. https://doi.org/10.1080/030549809022934563
- Sigmundsson, H., Haga, M., & Hermundsdottir, F. (2020). The passion scale: Aspects of reliability and validity of a new 8-item scale assessing passion. New Ideas in Psychology, 56, 100745. https://doi.org/10.1016/j.newideapsych.2019.06.001
- Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of Cronbach's alpha. *Psychometrika*, 74(1), 107–120. https://doi.org/10.1007/s11336-008-9101-0
- Sivan, E. (1986). Motivation in social constructivist theory. *Educational Psychologist*, 21(3), 209–233. https://doi.org/10.1207/s15326985ep2103_4
- Skinner, B. F. (1950). Are theories of learning necessary? Psychological Review, 57(4), 193–216. https:// doi.org/10.1037/h0054367
- Sorić, I., Penezić, Z., & Burić, I. (2017). The big five personality traits, goal orientations, and academic achievement. *Learning and Individual Differences*, 54, 126–134. https://doi.org/10. 1016/j.lindif.2017.01.024
- Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, 25(2), 173–180. https://doi.org/10.1207/s15327906m br2502_4
- Sulea, C., van Beek, I., Sarbescu, P., Virga, D., & Schaufeli, W. B. (2015). Engagement, boredom, and burnout among students: Basic need satisfaction matters more than personality traits. *Learning* and Individual Differences, 42, 132–138. https://doi.org/10.1016/j.lindif.2015.08.018
- Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2007). Using multivariate statistics (Vol. 5). Pearson.
- Talsma, K., Schüz, B., Schwarzer, R., & Norris, K. (2018). I believe, therefore I achieve (and vice versa): A meta-analytic cross-lagged panel analysis of self-efficacy and academic performance. *Learning and Individual Differences*, 61, 136–150. https://doi.org/10.1016/j.lindif.2017.11.015
- Tanzer, J. R. (2019). Developing authentic happiness: Growth curve models to assess lifelong happiness. The Journal of Positive Psychology, 16(1), 11–19. https://doi.org/10.1080/17439760. 2019.1689419
- Thoonen, E. E., Sleegers, P. J., Peetsma, T. T., & Oort, F. J. (2011). Can teachers motivate students to learn? *Educational Studies*, 37(3), 345–360. https://doi.org/10.1080/03055698.2010.507008
- Ting, Y. L. (2015). Tapping into students' digital literacy and designing negotiated learning to promote learner autonomy. *The Internet and Higher Education*, 26, 25–32. https://doi.org/10. 1016/j.iheduc.2015.04.004
- Trapmann, S., Hell, B., Hirn, J. O. W., & Schuler, H. (2007). Meta-analysis of the relationship between the big five and academic success at university. *Journal of Psychology*, 215(2), 132– 151. https://doi.org/10.1027/0044-3409.215.2.132
- Trask-Kerr, K., Chin, T. C., & Vella-Brodrick, D. (2019). Positive education and the new prosperity: Exploring young people's conceptions of prosperity and success. *Australian Journal of Education*, 63(2), 190–208. https://doi.org/10.1177/0004944119860600
- Trautwein, U., Lüdtke, O., Roberts, B. W., Schnyder, I., & Niggli, A. (2009). Different forces, same consequence: Conscientiousness and competence beliefs are independent predictors of academic effort and achievement. *Journal of Personality and Social Psychology*, 97(6), 1115–1128. https://doi.org/10.1037/a0017048
- Trespalacios, J., & Uribe-Florez, L. J. (2020). Developing online sense of community: Graduate students' experiences and perceptions. *The Turkish Online Journal of Distance Education TOJDE*, 21(1), 57–72.
- Tucker, B. (2012). The flipped classroom. Education Next, 12(1), 82-83.

- Vallerand, R. J., Blanchard, C., Mageau, G. A., Koestner, R., Ratelle, C., Léonard, M., Gagné, M., & Marsolais, J. (2003). Les passions de l'ame: On obsessive and harmonious passion. *Journal* of Personality and Social Psychology, 85(4), 756–767. https://doi.org/10.1037/0022-3514.85.4. 756
- Van Fleet, A. (1979). Learning to teach: The cultural transmission analogy. *Journal of Thought*, 14(4), 281–290.
- Varol, B., & Yilmaz, S. (2010). Similarities and differences between female and male learners: Inside and outside class autonomous language learning activities. *Proceedia - Social and Behavioral Sciences*, 3, 237–244. https://doi.org/10.1016/j.sbspro.2010.07.038
- Vedel, A. (2014). The big five and tertiary academic performance: A systematic review and metaanalysis. *Personality and Individual Differences*, 71, 66–76. https://doi.org/10.1016/j.paid.2014. 07.011
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Vygotsky, L. S. (1987). Thinking and speech (N. Minick, Trans.). In R. W. Rieber & A. S. Carton (Eds.), *The collected works of LS Vygotsky* (Vol. I, pp. 39–285). Plenum Press.
- Wandler, J. B., & Imbriale, W. J. (2017). Promoting undergraduate student self-regulation in online learning environments. *Online Learning*, 21(2), 1–16. https://doi.org/10.24059/olj.v21i2.881
- Wang, C., & Zhao, H. (2020). The impact of COVID-19 on anxiety in Chinese university students. Frontiers in Psychology, 11(1168), 1–8. https://doi.org/10.3389/fpsyg.2020.01168
- Wang, J. C. K., Ng, B. L. L., Liu, W. C., & Ryan, R. M. (2016). Can being autonomy-supportive in teaching improve students' self-regulation and performance? In W. C. Liu, J. C. K. Wang, & R. M. Ryan (Eds.), *Building autonomous learners* (pp. 227–243). Springer. https://doi.org/10. 1007/978-981-287-630-0_12
- WHO. (2020). WHO Director-General's opening remarks at the media briefing on COVID-19 11 March 2020. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarksat-the-media-briefing-on-covid-19---11-march-2020
- Wilcox, R. R. (2010). Fundamentals of modern statistical methods: Substantially improving power and accuracy (2nd ed.). Springer.
- Williams, T., & Williams, K. (2010). Self-efficacy and performance in mathematics: Reciprocal determinism in 33 nations. *Journal of Educational Psychology*, 102(2), 453. https://doi.org/10.1037/ a0017271
- Williamson, B. (2020). Making markets through digital platforms: Pearson, edu-business, and the (e) valuation of higher education. *Critical Studies in Education*. https://doi.org/10.1080/17508487. 2020.1737556
- Wong, J., Baars, M., Davis, D., Van Der Zee, T., Houben, G. J., & Paas, F. (2019). Supporting selfregulated learning in online learning environments and MOOCs: A systematic review. *International Journal of Human-Computer Interaction*, 35(5), 356–373. https://doi.org/10.1080/10447 318.2018.1543084
- Wrigley, T. (2019). The problem of reductionism in educational theory: Complexity, causality, values. Power and Education, 11(2), 145–162. https://doi.org/10.1177/1757743819845121
- Xiao, S., Yao, K., & Wang, T. (2019). The relationships of self-regulated learning and academic achievement in university students. SHS Web of Conferences, 60, 1–4. https://doi.org/10.1051/ shsconf/20196001003
- Yildirim, M., & Belen, H. (2018). The role of resilience in the relationships between externality of happiness and subjective well-being and flourishing: A structural equation model approach. *Journal of Positive School Psychology*, 3(1), 62–76.
- Yilmaz, R. (2016). Knowledge sharing behaviors in e-learning community: Exploring the role of academic self-efficacy and sense of community. *Computers in Human Behavior*, 63, 373–382. https://doi.org/10.1016/j.chb.2016.05.055
- Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. Educational Psychologist, 25(1), 3–17. https://doi.org/10.1207/s15326985ep2501_2
- Zimmerman, B. J., & Bandura, A. (1994). Impact of self-regulatory influences on writing course attainment. American Educational Research Journal, 31(4), 845–862. https://doi.org/10.3102/ 00028312031004845

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

Darrell Eckley is studying a Master of Psychology (Clinical) at the University of the Sunshine Coast. He is a Provisional Psychologist and conducts academic research in education and transdiagnostic formulation.

Andrew Allen PhD Candidate, is an Associate Lecturer in Clinical Psychology in the School of Health and Behavioural Sciences at the University of the Sunshine Coast. He is a registered Clinical Psychologist and conducts academic research in the areas of clinical psychology, cognitive psychology, and human sexuality.

Prudence Millear Phd, is a Lecturer in Psychology at the University of the Sunshine Coast and Psychology Honours Program Coordinator. She conducts research in the areas of developmental psychology and occupational health psychology, with interests in factors that influence the success or not of relationships, developing and maintaining meaningful work, and healthy ageing.

Karina Tirsvad Rune PhD, is a Lecturer in Psychology in the School of Health and Behavioural Sciences at the University of the Sunshine Coast. She is a Provisional Psychologist and conducts academic research in the areas of psycho-oncology, environmental psychology, and health behaviours.