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Education Technologies and COVID-19: Experiences and Lessons Learned

Student Engagement and Learning Approaches During COVID-19: The Role of Study Resources, Burnout Risk, and Student Leader–Member Exchange as Psychological Conditions

Melissa Reynell van der Ross, PhD
University of Pretoria, Pretoria, South Africa
https://orcid.org/0000-0002-8008-5950

Chantal Olckers, PhD
University of Pretoria, Pretoria, South Africa
https://orcid.org/0000-0001-5592-3951

Pieter Schaap, PhD
University of Pretoria, Pretoria, South Africa
https://orcid.org/0000-0002-8293-5787

Contact: reynellvanderross@gmail.com

Abstract

Objectives: The primary objective of this study was to explore the interplay of psychological conditions that influenced personal engagement among university students. As a theoretical lens through which to investigate this, the study used the job demands-resources model, the study demands-resources model, and the leader–member exchange theory. This study further aimed to explore outcomes that supported students in becoming lifelong learners (i.e., deep-learning approach).

Method: Participants were undergraduate students registered at a South African university. We used a purposive, non-probability sampling strategy and employed a cross-sectional survey research design. This study used Mplus version 8.6 for the statistical analyses.

Results: Results showed that the psychological conditions of meaningfulness (study resources), availability (burnout risk), and safety (student–leader–member exchange) influenced student engagement. In addition, the results showed that study demands were positively associated with student engagement, although this association can be regarded as small. Furthermore, study resources and student engagement were associated with a deep approach to learning.

Conclusions: Findings from the present study demonstrated that Kahn's theory carried implications beyond the workplace and held true in a student learning environment. Further, an exploration of the psychological conditions that led to engagement showed that the job demands-resources model and the study demands-resources model could be used to operationalise study resources as psychological meaningfulness and burnout risk as availability. Similarly, in the context of exploring the student-lecturer relationship, student leader–member exchange could be operationalised as psychological safety.

Implication for Practice: Leaders in higher education are encouraged to focus not only on ensuring that students receive adequate support in terms of structures and physical resources during periods of uncertainty, such as the global COVID-19 pandemic, but to adopt a holistic approach that includes considering all the psychological conditions that encourage and promote students' engagement.

Keywords: *Burnout risk, deep and surface approaches to learning, student engagement, study demands-resources, student leader–member exchange*

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Introduction

Against the backdrop of an increase in withdrawal behaviour among students, a decline in student well-being (Auerbach et al., 2018), an increase in student stress levels (Robotham, 2008), and student experiences of academic isolation during the COVID-19 pandemic (Visser & Law-Van Wyk, 2021), it becomes imperative to explore aspects which, according to positive psychology, would promote a more productive and fulfilling life (Seligman & Csikszentmihalyi, 2000). In this regard, Kotera and Ting (2019) stated that engagement is a positive psychological construct that is of particular importance in the higher education (HE) context as far as student academic activities are concerned.

Engagement has been found to assist in performing one's work to the fullest (Bakker, 2017; Kahn, 1990), being creative, connecting to the work role and other people, focusing on moving ahead with work, and putting in an effort (Kahn, 1990). Although Kahn's conceptualisation of personal engagement is structured around employees in the workplace, scholars have put forth that, from a psychological stance, the core academic activities of university students can be considered as "work" as these activities are organised, coercive, and structured (Cilliers et al., 2018; De Jonge et al., 2019; Ouweneel et al., 2011).

Theoretical Framework

The present study drew on positive psychology to explore the conditions that enable the positive psychological construct of engagement (Kotera & Ting, 2019; Seligman et al., 2005) among students within HE. In so doing, this study drew on theories and models that aim to explain antecedents to engagement. Accordingly, the job demands-resources (JD-R) model (Demerouti et al., 2001) and the study demands-resources (SD-R) model (Mokgele & Rothmann, 2014) underpinned this research study. The JD-R model provides a basis for understanding the role of work conditions (job demands and resources) as antecedents to burnout and engagement (Crawford et al., 2010). The model explains how job demands cost or consume energy, which leads to burnout, whilst resources are functional in achieving goals and promoting engagement (Bakker & Demerouti, 2017; Jackson et al., 2006). The SD-R model is based on the JD-R model and explains the effects of study characteristics (study demands and study resources) on student burnout and engagement (Mokgele &

Rothmann, 2014). The study further drew on Kahn's (1990) theory of personal engagement and extended this theory beyond the employee/employer context, to focus on students in HE.

Contribution of the Study

To better understand the circumstances that allow positive constructs such as engagement to flourish, in accordance with the premise of positive psychology (Seligman et al., 2005), the present study investigated the psychological conditions that enable engagement as conceptualised by Kahn (1990). This study made use of (a) the JD-R model (Bakker & Demerouti, 2017), a model which is regarded as one of the most solid empirical foundations in clarifying job characteristics that underlie engagement in the work context (Mercali & Costa, 2019); (b) the SD-R model (Mokgele & Rothmann, 2014), a model developed to understand the effects of study characteristics on students; and (c) the leader–member exchange (LMX) theory (Graen et al., 1982) as a theoretical lens through which to conceptualise the lecturer–student relationship, which is regarded as in its infancy (Farr-Wharton et al., 2018).

The aim of this study was to better understand the construct of student engagement. The promotion of student engagement is important, as it is believed to enhance students' abilities not only to perform well academically but also to learn how to learn and to become lifelong learners in a global and knowledge-based society (Taylor & Parsons, 2011). As a student's approach to learning has profound implications beyond the classroom, this study aimed to gain an understanding of learning quality in HE (Baron & Corbin, 2012; Cai & Liem, 2017; Fryer, 2017) and to explore student learning approaches by extrapolating from work done using the JD-R model (Bakker & Demerouti, 2017) or in this case the SD-R model (Mokgele & Rothmann, 2014). In so doing, this study endeavoured to extend the existing understanding of how student engagement influenced learning approaches and processes that reflected student intentions to understand the meaning of their work (Campbell & Cabrera, 2014; Fourie, 2003). Findings from the study should offer support to leaders in HE to consider the role of both engagement and learning approaches in addressing the quality of student learning and academic performance.

Literature Review and Research Hypotheses

Defining Student Engagement

Student engagement has become an area of priority to HE institutions globally (Groccia, 2018; West & Halvorson, 2019), which explains the existence of a wide variety of definitions of student engagement (Mandernach, 2015). Groccia (2018) noted that Ralph Tyler, who was one of the pioneers in the study of student engagement during the 1930s, showed that time spent on tasks had positive effects on learning. Kuh (2003) described student engagement as the time and energy that students devote to educational activities, which include academic activities outside the classroom and activities in which institutional policies and practices encourage them to participate. Axelson and Flick (2011) described student engagement as the level of involvement and interest students show in their learning and their level of connectedness with their classes, peers, and the institution.

Kahn (2014) indicated that student engagement is characterised by the contribution students make to their learning, which includes the time, commitment, effort, and resources they invest. Further, student engagement can be seen as reflecting similar investments by the academic institutions to optimise the student learning experience and performance. Scholars have also described student engagement as a combination of diligence, willingness to participate in learning activities, involvement, and dedication toward studies (Mokgele & Rothmann, 2014; Salanova et al., 2010). The concept was further conceptualised by Gunuc and Kuzu (2015) as consisting of campus engagement, which describes the value students attach to their education and their sense of belonging; and class engagement, which describes cognitive, behavioural, and emotional reactions to both out-of-class and in-class educational activities. In other words, student engagement reflects investment in learning, participation in academic activities, and attitude to the teacher or class (Gunuc & Kuzu). In a more recent study, Lee et al. (2019), in measuring student engagement in an online learning environment, conceptualised student engagement as being comprised of six dimensions. These dimensions are psychological motivation (feelings of being motivated and interested in following an online learning course), peer collaboration (attempts to collaborate with peers, build knowledge, and discuss knowledge with peers), cognitive problem-solving (the use, application and understanding of knowledge, interactions with instructors (communication with the instructor of the online course), community support (emotional sense of belonging to the group of students enrolled for the online course), and learning management (management of learning and participation in the course e.g., planning to attend online classes and submit all assignments).

Steele and Fullagar (2009) believed that there is no consensus about defining engagement and that most existing definitions lack a conceptual foundation or confuse outcomes or antecedents of engagement with their facets. It seems, however, that scholars agree that student engagement includes a range of cognitive, affective, and behavioural components of the student learning experience (Burch et al., 2015; Cai & Liem, 2017; Lee et al., 2019; Handelsman et al., as cited in Mandernach, 2015). They describe affective components of student engagement as being the feelings or emotional engagement during the learning process (e.g., enjoyable states of mind), cognitive components as being the thinking strategies used to process the information learned, and behavioural components as being the overt involvement of students during academic tasks. These views are in alignment with Kahn's (1990) conceptualisations relating to personal engagement and disengagement in the workplace.

Burch et al. (2015) developed a student engagement scale based on Astin's (1984) student involvement theory and Kahn's (1990) grounded theory of personal engagement and disengagement. According to Astin, student involvement denotes the quantity and quality of psychological and physical energy that students devote to the academic experience as well as the effectiveness of institutions' educational practices and policies that are directed toward increasing student involvement. Burch et al.'s (2015) student engagement scale is built on the definition that student engagement is a multidimensional construct of emotional, physical, and cognitive engagement both in and out of class. This conceptualisation seems to be supported by more recent studies (e.g., Groccia, 2018) according to which student engagement operates on multiple cognitive, behavioural, and affective levels, both in and out of the classroom. For the purposes of the present study, we adopted Burch et al.'s (2015) definition of student engagement as it is grounded in a theoretical framework that is in alignment with the objectives of this study, and, further, as it can be regarded as inclusive of Lee et al.'s (2019) six dimensions of an online learning environment. As described earlier, these dimensions include psychological motivation (feelings of motivation and interest), community support or the sense of belonging to a group (emotional engagement), cognitive problem-solving (cognitive engagement), peer collaboration or attempts to collaborate, interactions with instructors, and learning management, which refers to the students' participation in the course (physical engagement).

The Relationship Between Study Demands-Resources, Burnout Risk, and Student Engagement

In response to the observation of Robotham (2008) that the interpretation or perception of high demands instead of the actual demands themselves can potentially cause harm, Salanova et al. (2010) asserted that it is essential to understand how students perceive their demands and resources. To gain such an understanding, this study applied the JD-R model. The JD-R model has been tested not only among staff in the HE sectors (e.g., Bakker et al., 2005; Jonasson et al., 2017; Rothmann & Jordaan, 2006; Rothmann et al., 2006; Williams et al., 2017), but also among students (e.g., Mokgele & Rothmann, 2014; Robins et al., 2015). Like the JD-R model (Bakker & Demerouti, 2017; Demerouti et al., 2001), the SD-R model (Mokgele & Rothmann, 2014) proposes that study resources promote engagement, as they play a key role in motivating students and keeping them from withdrawal behaviour. The SD-R scale measures study resources as consisting of lecturer support, peer support, growth, and information accessibility.

Important in the context of the present study is Kahn's (1990) assertion that three conditions shape whether a person would personally engage or not. The first condition is that of *meaningfulness*, which is the state of feeling that one is valued, is a worthy person, and is not taken for granted. This state of feeling is influenced by (a) whether one's work tasks are challenging, allow for learning, and provide a sense that one is competent; (b) whether one's role as an individual is central to or is needed by one's institution; and (c) work interactions with co-workers and clients. Likewise, the study resources as conceptualised by Mokgele and Rothmann (2014) and measured by the SD-R scale address the aspects of challenging tasks (e.g. "Do your studies make sufficient demands on your skills and capacities?"), learning (e.g. "Do your studies offer you opportunities for personal growth and development?"), and provision of a sense of competence (e.g. "Do your studies give you the feeling that you can achieve something?"). The SD-R scale further addresses work interactions with co-workers or peers (as in the case of the present study) (e.g. "Can you count on your fellow students when you run into difficulties in your studies?"), and whether students feel valued or central to the institution in terms of management decisions made in the specified course (e.g. "Are you kept up to date about issues within your module?" and "Is the decision-making processes within the module/department/faculty clear to you?"). Mokgele and Rothmann (2014) further indicated that feedback and support from lecturers and opportunities for growth and development affect psychological states such as meaningfulness. Therefore, the present study viewed study resources, as conceptualised in the SD-R scale (Mokgele & Rothmann), as addressing the criteria relevant to psychological meaningfulness. Thus, based on Kahn's (1990) conceptualisation that psychological meaningfulness is one of the antecedents to engagement, and based on the finding of empirical studies (e.g., Salmela-Aro & Upadyaya, 2014) that study-related resources can lead to engagement within a school context, as well as on the finding of Robins et al. (2015) that optimal study resources lead to increased levels of student engagement, we postulated the following hypothesis for the present study:

H1: There is a statistically significant positive relationship between study resources and student engagement.

Like the JD-R model, the SD-R model (Mokgele & Rothmann, 2014) proposes that time and study pressure demands drain student energy and cause fatigue or burnout. Zeijen et al. (2021) confirmed that study demands (e.g., study workload, emotional demands, and study–home interference) are positively related to burnout of master's degree students. Similarly, an earlier study by Robins et al. (2015) found that study demands were positively related to burnout. Robins et al. also found a negative relationship between study demands and engagement. Other studies within a South African context corroborated the finding that study demands were significantly related to engagement (e.g., Cilliers et al., 2018). A more recent meta-analysis (Rattrie et al., 2020) showed associations between demands and engagement. Accordingly, the present study postulated the following hypotheses:

H2: There is a statistically significant positive relationship between study demands and burnout risk.

H3: There is a statistically significant negative relationship between study demands and student engagement.

The Copenhagen Burnout Inventory (Creedy et al., 2017) categorises burnout as personal and work-related burnout. Personal burnout refers to the degree of psychological and physical exhaustion or fatigue an individual experiences, and work-related burnout to the degree of psychological and physical exhaustion or fatigue the individual perceives as related to their work. Maroco and Campos (2012) referred to the latter category as studies-related burnout within a student context. Salmela-Aro and Upadyaya (2014) found that school burnout, which they described as the experience of feelings of inadequacy and exhaustion due to school demands, negatively influenced schoolwork engagement a year later. A study among PhD students similarly found that high burnout was related to low levels of engagement (Kusurkar et al., 2020).

According to Kahn (1990), the second condition that influences personal engagement is that of *availability*. Availability describes the physical and psychological resources people have available considering distractions experienced, such as depletion of physical and emotional energy, outside lives or personal lives, and insecurity. Burnout seems to address components related to the depletion of physical and emotional energy and outside lives as per the availability condition specified by Kahn (1990). Accordingly, this study operationalised burnout risk as psychological *availability* and postulated the following hypothesis:

H4: There is a statistically significant negative relationship between burnout risk and student engagement.

The Role of Physical Resources During COVID-19

Worldwide, the COVID-19 pandemic plunged educators and students, specifically universities for the present study, into the unprecedented educational scenario of having to transition to either purely online or blended learning methods (Perets et al., 2020). Neuwirth et al. (2020) indicated that this transition has resulted in changes in student behaviours in classes; they have become predominantly inattentive, many are not physically/visually or mentally present, and they ask fewer questions, compared to the on-campus, face-to-face classes before the pandemic. Neuwirth et al. stated that educators often rely on visual feedback from students to better gauge their understanding of the concepts in real-time. Consequently, the perceived invisibility of students (i.e., turning off their laptop cameras) severely constrains teaching. The authors did, however, list a variety of difficulties that could underpin student behaviour, such as a lack of quiet or private areas at home, distractions or noise in the background, hesitancy to let others see their home environment, and lack of online access and availability of physical resources. This is supported by findings from Tigaa and Sonawane (2020) that physical resources, such as electricity infrastructure and reliable internet access, influence student engagement. Accordingly, the following hypothesis was postulated:

H5: There is a statistically significant positive relationship between physical resources, such as adequate study conditions at home, access to a stable internet, electricity, and devices, and student engagement.

The Relationship Between Student Engagement, Deep Learning, and Academic Performance

Student engagement has been regarded as a key component of student success in higher education institutions (Boulton et al., 2019; Kahn, 2014). Salanova et al. (2010) found that engagement was an important factor, even more important than study burnout, in predicting future performance. Engagement also plays an important role in the quality of student work (Kahu, 2013) and in persistence and retention (Schreiber & Yu, 2016). Further, student engagement is regarded as a key factor in promoting outcomes such as academic achievement, the creation of a positive student experience, and the development of lifelong learners (Baron & Corbin, 2012; Cai & Liem, 2017; Kahn, 2014). Based on these findings, the present study postulated the following hypothesis:

H6: There is a statistically significant positive relationship between student engagement and academic performance.

As regards the benefits that have been associated with fostering lifelong learning, Floyd et al. (2009) found a significant and positive relationship between student engagement and a deep-learning strategy. These authors indicated that deep learning occurs in cases where students perceive themselves as engaged and the course content as valuable. Correspondingly, Bevan et al. (2014) contended that student engagement with course material is critical in fostering deep learning. Deep learning, which is described as both intellectual and emotional (West & Halvorson, 2019), is regarded as the intrinsically motivated intention of students to understand the meaning of the work, to try and relate the work to ideas in other disciplines or subjects, and to organise the work holistically (Fourie, 2003; West & Halvorson, 2019). Surface learning, in contrast, is regarded as a more passive approach to learning, one that is characterised by memorising or reproducing that which was read or heard in a lecture without necessarily making sense of the work (Fourie, 2003). Accordingly, the present study postulated the following hypotheses:

H7a: There is a statistically significant positive relationship between student engagement and a deep-learning approach.

H7b: There is a statistically significant negative relationship between student engagement and a surface-learning approach.

A deep approach to learning has been described as a process of discovery, understanding, and growth rather than as simply a process of knowledge transfer (Platow et al., 2013). Deep-learning approaches are further considered as playing an important role in student outcomes such as persistence, the ability to more effectively process information (Campbell & Cabrera, 2014), academic achievement (Zhang, 2000), and the attainment of better quality learning and development (Fourie, 2003). Accordingly, the present study postulated the following hypotheses:

H8a: There is a statistically significant positive relationship between a deep approach to learning and academic performance.

H8b: There is a statistically significant negative relationship between a surface approach to learning and academic performance.

The Influence of Student–Leader-Member Exchange (Psychological Safety) on Engagement

Basson and Rothmann (2019) indicated that student perceptions of their assets, workload, and support from lecturers are of crucial importance in determining whether they flourish or languish in their studies. Eloff et al. (2021) affirmed that lecturers play a substantial role in the well-being of students. Farr-Wharton et al. (2018) argued that leader-member exchange (LMX) should be a central consideration in establishing a learner-centred pedagogy, but that the use of LMX as a theoretical lens to conceptualise the lecturer–student relationship is still in its infancy. LMX, which concerns the perception of the member or subordinate and their evaluation of the quality of the relationship with the leader, focuses on interpersonal relationships between superiors (leaders) and their followers (members) within the boundaries of an organisational structure (Kim & Yi, 2018). LMX theory postulates that leaders/superiors develop different relationships with members/followers and that this difference is reflected in the quality of the exchange relationship (Myers, 2006; Power, 2013). High-quality exchange relationships between leaders/superiors and members/followers are referred to as in-group relationships, whereas low-quality exchange relationships between the two parties are referred to as out-group relationships (Myers, 2006).

Relevant meta-analytic reviews have consistently found correlations between LMX and member commitment, efforts in terms of job performance, and intentions to quit (Dulebohn et al., 2012; Gerstner & Day, 1997). Studies have also shown that LMX is positively related to social job resources (Radstaak & Hennes, 2017) and negatively related to emotional exhaustion (Lai et al., 2018) and demands such as role overload (Tang & Vandenberghe, 2021). Furthermore, LMX has been shown to moderate the positive relationship between role overload and psychological strain, such that role overload is less positively related to strain when LMX levels are high (Tang & Vandenberghe, 2021). Lam et al. (2018), expanding on their finding that emotional job demands are positively related to emotional engagement where LMX is high, reported that employees regard line managers' guidance and support (high LMX) as a resource that allows them to handle emotionally demanding situations. Farr-Wharton et al. (2018) referred to student–LMX as the relationship which is formed during learning activities such as lectures, communication in online forums, and interactions between lecturers or tutors and their students. Based on the considerations by Lorah and Wong (2018), in the context of this study, student–LMX can similarly be regarded as a possible moderator.

The third condition that has an influence on personal engagement is that of psychological *safety*, which describes the state of feeling no fear to express oneself because doing so would not have negative consequences for one's career or self-image (Kahn, 1990). The feeling of psychological safety is influenced by supportive interpersonal relationships, management style, and organisational norms or expectations (the general and appropriate ways of behaving or working, including predictability) (Kahn, 1990). According to Kahn, norms are based on the rules or cues that govern behaviour in a specific context. As student–LMX denotes the perception of students regarding how positive, reciprocal, and supportive the relationships with their lecturers are (Farr-Wharton et al., 2018), and as in-group or out-group exchange relationships affect students' motivation to communicate with their educators (Myers, 2006), one can argue that students' evaluation of their lecturers' management style (i.e. as supportive, consistent, and non-hypocritical) will influence the student–LMX relationship and determine the extent to which students feel safe to express themselves without fear of negative consequences. Thus, the present study deemed that student–LMX addressed components of psychological safety. In accordance with Kahn's directive to explain engagement by exploring the interaction of psychological conditions, the present study considered student–LMX as a moderator in the associated relationships with engagement as proposed in the SD-R model. Accordingly, this study put forth the following hypotheses:

H9a: Student–LMX, which carries aspects of psychological safety, moderates the relationship between study resources and engagement, such that high student–LMX strengthens the positive relationship between study resources and student engagement.

H9b: Student–LMX moderates the relationship between physical resources and student engagement, such that high student–LMX strengthens the positive relationship between adequate physical resources and student engagement.

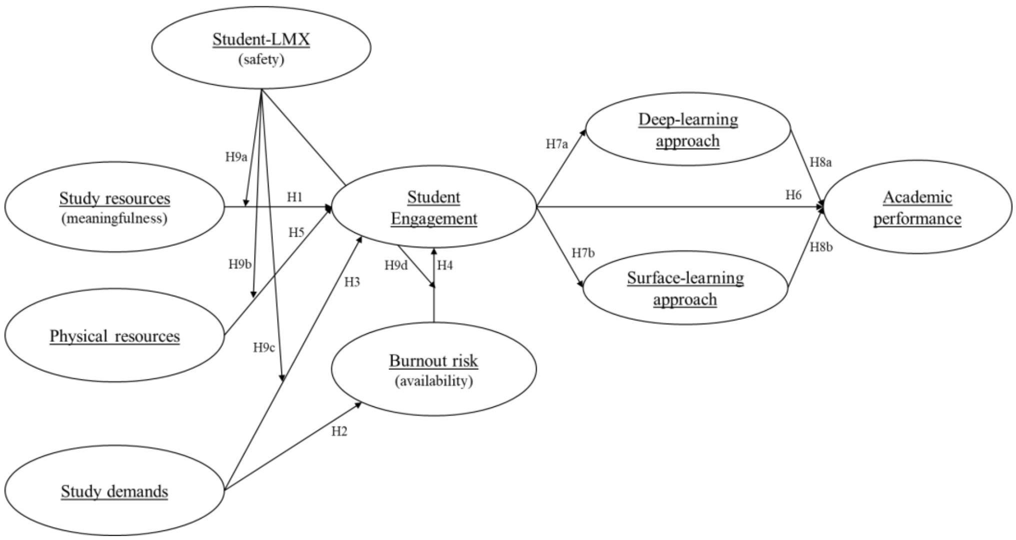
H9c: Student–LMX moderates the relationship between study demands and student engagement, such that high student–LMX acts as a buffer against the negative effect of study demands on student engagement.

H9d: Student–LMX moderates the relationship between burnout risk and student engagement, such that burnout risk is less (vs. more) negatively related to student engagement at high student–LMX levels.

The Conceptual Framework

The hypothesised framework developed for this study is presented in Figure 1.

Figure 1. *Conceptual Framework (Hypothesised Model—Model 1)*



Note: LMX, leader-member exchange

Method

Sample and Procedure

Participants were undergraduate students registered at a South African university. Quantitative methods were used as the strategy of inquiry. We used a purposive, non-probability sampling strategy and employed a cross-sectional survey research design. The present study formed part of a larger multilevel research project that involved students registered for a specified second-semester undergraduate module taught by the participating staff member during 2020. After having obtained permission from the relevant institution to conduct the study, we distributed electronic surveys via notices in virtual learning spaces (Blackboard, WhatsApp) and SMSs. Consent to take part in the survey was obtained, and of the 5,294 students who agreed to participate, only 1,663 could be included in the study, due to missing values on the variables of interest. Males comprised 44%. Most students were African (93%), fell within the age range of 20 to 22 years (38%), and were enrolled for degrees in the Faculty of Engineering, Built Environment, and Information Technology (47%). The characteristics of the participants are provided in Table 1.

Table 1. *Characteristics of Participants* (N = *1,663)*

Item	Category	Percentage
Gender	Male	44%
	Female	56%
Age range	17–19	14%
	20–22	38%
	23–25	24%
	26–28	11%
	29–31	6%
	Older	7%
Ethnic group	African	93%
	Coloured	3%
	White	3%
	Indian or Asian	–
	Other	–
	Missing values	1%
Home language	English	19%
	Afrikaans	4%
	isiZulu	4%
	isiXhosa	10%
	Sepedi	1%
	Setswana	12%
	Sesotho	46%
	Xitsonga	1%
	siSwati	1%
	Tshivenda	1%
	isiNdebele	–
	Other: Please specify	–
Faculty	Faculty of Engineering, Built Environment, and Information Technology	47%
	Faculty of Health and Environmental Sciences	3%
	Faculty of Humanities	13%
	Faculty of Management Sciences	37%

Instrumentation

Study Demands and Resources

We used the 23-item Study Demands and Resources Scale (Mokgele, 2014). The study demands scale comprises five items related to time and study pressure. The study resources scale comprises four dimensions, namely, lecturer support, peer support, growth, and information accessibility. Both the scales were rated on a 4-point rating scale ranging from 1 = "never" to 4 = "always," and sample items included "Do you have too much work to do?" (i.e., study demands), and "If necessary, can you ask your fellow students for help?" (i.e., study resources, growth). Mokgele and Rothmann (2014) reported reliability above 0.70 for all the resources sub-scale dimensions, and for the study demands sub-scale, moderate (0.61) reliability was reported.

Physical Resources

In alignment with studies showing the importance of physical resources during the COVID-19 pandemic, the present study included items on physical resources. Four items, which were rated on a 4-point rating scale ranging from 1 = "never" to 4 = "always" were included, and a sample item was, "Are your study conditions adequate at home to allow for the attendance of online classes where needed and completion of academic work from home?"

Burnout Risk

The 19-item Copenhagen Burnout Inventory was used to measure student burnout risk. Item wording was adapted for the student context, and sample items included, "How often do you feel worn out?" (i.e., personal burnout), "Do your studies frustrate you?" (i.e, work-related burnout adapted to address study-related burnout), and "Does it drain your energy to work with peers?" (i.e., personal burnout adapted to address peer-related burnout) (Kristensen et al., 2005). Past studies reported the following Cronbach's alpha coefficients for the subscales: $\alpha = 0.82$ (client-related burnout), $\alpha = 0.85$ (personal burnout), and $\alpha = 0.87$ (work-related burnout) (Johnson & Naidoo, 2013).

Student Engagement

The 24-item Burch Engagement Survey for Students (Burch et al., 2015) was used to measure student engagement, as this measure is in alignment with the definition of engagement adopted for the study. The scale measures four dimensions, namely emotional engagement, physical engagement, cognitive engagement in class, and cognitive engagement out of class, and includes the following sample items: "I feel energetic when I am in this class/attending a lecture (online)" (emotional engagement), "I exert my full efforts toward this class/course" (physical engagement), "When I am in the classroom for this module, via online platforms or traditional face-to-face classes, I pay a lot of attention to the lecture discussion and activities" (cognitive engagement in class), and "When I am reading or studying material related to this class/course, I focus a great deal of attention on class discussion and activities" (cognitive engagement out of class). The scale was adopted from the job engagement scale (Rich et al., 2010) and adapted to reflect the online/blended learning environment necessitated by the COVID-19 pandemic. A 5-point rating scale was used ranging from 1 = "strongly disagree" to 5 = "strongly agree." Cronbach's alpha coefficients were all above the recommended 0.70 and were as follows: $\alpha = 0.91$ (emotional engagement), $\alpha = 0.93$ (physical engagement), $\alpha = 0.96$ (cognitive engagement in class), and $\alpha = 0.96$ (cognitive engagement out of class) (Burch et al., 2015).

Approach to Learning

The approach to learning was measured using the revised 20-item, two-factor Study Process Questionnaire (R-SPQ-2F) (Biggs et al., 2001). This scale, which measures deep- and surface-learning approaches, contains four subscales (deep motive, surface motive, deep strategy, and surface strategy). The deep approach to learning comprises the subscale of deep motive (of which an example item is, "I find that, at times, studying gives me a feeling of deep personal satisfaction") and the subscale of deep strategy (of which an example item is, "I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied"). The surface approach to learning comprises the subscale of surface motive (of which an example item is, "My aim is to pass the programme requirements while doing as little work as possible") and the subscale of surface strategy (of which an example item is, "I only study seriously what's given out in class or the course outlines"). The four subscales were scored on a 5-point scale ranging from 1 = "never or rarely true of me" to 5 = "always or almost always true of me." Cronbach's alpha coefficients of the subscales were α = 0.62 (deep motive), α = 0.63 (deep strategy), α = 0.72 (surface motive), and α = 0.62 (surface strategy) (Biggs et al., 2001).

Academic Performance

Marks for the specified semester module taught by the participating lecturer were used as a measure of their academic performance. The final semester mark percentage for the specified module was used as an assessment of knowledge of the module content covered during the semester.

Student–Leader-Member Exchange (LMX)

In alignment with work done by Farr-Wharton et al. (2018), the present study measured student–LMX using an adapted version of the seven-item LMX scale (Graen & Uhl-Bien, 1995). We measured the items using a 5-point Likert scale, and sample items included, "The lecturer of the specified module ...—would be willing to help me in their own time" and "encourages a good learning relationship." Farr-Wharton et al. (2018) reported Cronbach's alpha of 0.90 for student–LMX.

Data Analysis

In this study we used Mplus version 8.6 statistical software for conducting structural equation modeling and followed a two-stage approach in the data analysis (Lu et al., 2011). Firstly, confirmatory factor analysis (CFA) was employed to confirm the factor validity and psychometric properties of the measures used in this study. Measurement models that allowed for the univocal scoring of each of the measures were tested using CFA and MLR estimation for non-normal data. Optimally weighted factor scores that represent the factor loadings in the confirmed measurement models were derived using the regression approach in Mplus. Secondly, the factor scores were included in the structural models tested that represent the hypothesised relationships between the measured constructs.

In the present study, all popular indices were reported for the models tested as a matter of convention and where degrees of freedom were low in models, the CFI and SRMR played a more decisive role in judging model fit (Kenny et al., 2015; McNeish et al., 2018; McNeish & Hancock, 2018). Accordingly, model fit was appraised as acceptable in the following cases: a CFI value above 0.90 but preferably above 0.95, a SRMR value preferably less than 0.08, a RMSEA value below 0.08, and a TLI value above 0.90 but preferable 0.95 (Hu & Bentler, 1999; Olckers & Van Zyl, 2019). Model fit was examined in combination with residual covariance matrices and reported in alignment with the theoretical framework that supports the results (MacCallum, 1990). Hayduk et al. (2007, p. 843) argued that a theoretical understanding of models is best enhanced by "diagnostic evidence accompanying a model's failure to fit" and can be extracted from the residual covariance matrices. Hayduk et al. (2007) further suggested that model modifications should not be dismissed where substantiating evidence or theory is strong. Where model modifications were made in this study, they were done conservatively and transparently and were supported by solid theoretical evidence (MacCallum et al., 1992).

To assess the internal structure of the scales, the McDonald's omega coefficient was used, with values of 0.70 and 0.80 deemed as acceptable and good (Crutzen & Peters, 2017; Dedeken et al., 2020; Feisst et al., 2019). Factor determinacy coefficients were calculated and should be high (>0.80) to ensure the factor score is a valid and reliable substitute for the latent factor and does not produce biased estimates in the structural model (Wang & Wang, 2020). Effect sizes of correlation coefficients were interpreted as small (r = 0.10), medium (r = 0.30), and large (r = 0.50), in accordance with the guidelines provided by Cohen (1988).

The bootstrapping technique for calculating measurement error is not available in Mplus with the maximum likelihood robust (MLR) estimation procedure for non-normal data. Thus, the delta method for estimating robust standard errors with a sandwich estimator was used for non-normal data, providing standard errors like those of the bootstrapping technique (Muthén & Muthén, 2017). To establish moderating and mediation effects in the models tested, the following were considered: 1) whether the beta coefficient of the interaction term was significant (Lam et al., 2018), and 2) whether the confidence intervals (CIs) were set at a level of 95% did not include zero (Zhao et al., 2010).

Results

This section reports on data screening for outliers, sample distribution statistics, the results relating to the evaluated measurement models, and the results of the structural models tested.

Data Screening and Sample Distribution Statistics

Students had to be matched with the relevant module lecturer for purposes of completing the student–LMX measure. As a result of non-matches or missing data, the sample was reduced to 1,605. The data was further checked for multivariate outliers using the Mahalanobis distance test (Tabachnick & Fidell, 2013). A total of 11 statistically significant multivariate outliers were removed from the data set using a conservative $\chi 2$ critical probability value of 0.001, resulting in a total sample of 1,594 students.

The univariate indicators of skewness and kurtosis (see Table 2) indicated that the requirement of univariate normality (skewness and kurtosis = > -1 and < +1) was not met for several variables. More importantly, Mardia's multivariate normality tests for skewness (4.73) and kurtosis (72.30) were not met (Mardia's kurtosis ≤ 4) (Anderson & Gerbing, 1988). All the variables were standardized (which means *Z* values with a mean of 0 and a standard deviation of 1) for the purpose of the analysis.

The marks that the students received in the specified second-semester module code were used as a measure of their academic performance (variable 8). The results obtained showed 46% missing values because some students had indicated incorrect module codes (e.g., by indicating the course or module name instead of the code or only the letter code without a number, or by not providing a module code). The sample size for the academic performance measure was 853. However, all other variables are based on the total sample of 1,594.

Table 2. *Skewness/Kurtosis Statistics for the Variables Used in the Study*

Variable		*N*	Skewness	Kurtosis
a)	Study resources	1594	-1.14	0.95
b)	Physical resources	1594	-0.63	-0.08
c)	Study demands	1594	-0.66	0.15
d)	Burnout risk	1594	0.16	-0.58
e)	Student engagement	1594	-1.06	2.10
f)	Student–LMX	1594	-0.52	-0.58
g)	Deep-learning approach	1594	-0.19	-0.55
h)	Surface-learning approach	1594	0.46	-0.15
i)	Academic performance	853	-1.40	2.50

Note: N = participants in the study sample for the given variable

Testing the Measurement Models

All the measurement models tested in this study represented first-order unidimensional factor models except for the burnout risk construct which represents a second-order factor model. The detailed results of the measurement models for the variables used in this study are depicted in Table 3 (N = 1,594). The table provides an overview of the fit statistics per the factor model, the construct measured, the relevant subscales or facets, the number of items per construct measured, and the number of items per facet. All models showed acceptable to good model fit and well-defined factor structures (mean factor loadings were between 0.54 and 0.79) that can be univocally scored. The model fit evaluations for the factor models tested are as follows:

a) Study resources (18 items)—good fit.
b) Physical resources (4 items)—good fit.
c) Study demands (5 items)—acceptable fit.
d) Burnout risk (18 items)—acceptable fit.
e) Student engagement (24 items)—good fit.
f) Student–LMX (7 items)—good fit.
g) Deep-learning approach (10 items)—good fit.
h) Surface-learning approach (10 items)—acceptable fit.

However, the results reported were after post-hoc model modifications were made for selected models where misfit was evident to ensure acceptable model fit and factorial validity. More specifically, the modified models were burnout risk, student engagement, student–LMX, deep-learning approach, and surface-learning approach.

The rational for modifying the models is vested in the fact that unidimensional CFA models consisting of numerous items are highly restrictive in nature and highly sensitive to misfit where the misfit may have only minor substantive meaning or can be considered a method artifact of measurement with negligible consequences (Byrne et al., 1989; Marsh et al., 2004; Reise et al., 2013). Method artifacts can be attributed to reversed item scoring, items containing similar words or phrases, or the effect of adjacency where items that measure the same construct are grouped in proximity of each other. Respondents rate these items similarly while avoiding cognitive dissonance which in turn results in correlated residuals (Loiacono & Wilson, 2020; Podsakoff et al., 2012).

The models that showed unacceptable fit were modified by the post hoc freeing of correlated residuals that can be theoretically or pragmatically justified, such as method artifacts (Byrne et al., 1989; Jackson et al., 2009; Loiacono & Wilson, 2020; Podsakoff et al., 2012). On the burnout risk model, one item which was reverse scored was removed because its factor loading was low (0.32). The effect of method artifacts that was explained earlier contributed to the need to free the residuals of two adjacent items by allowing them to be correlated. Furthermore, method artifacts were present in the following models and the items were allowed to correlate: Two items on the student engagement model, the first three items on the student–LMX model, two items on the deep-learning approach model and two item pairs on the surface-learning approach model.

McDonald's omega reliability coefficients for the variables (factor model scores) reported in Table 4 were all above 0.70, which demonstrated acceptable to good reliability. An exception was the study demands factor model (ω = 0.68), which showed a value just below 0.70 (Crutzen & Peters, 2017; Dedeken et al., 2020; Feisst et al., 2019). Moreover, the factor determinacy values reported in Table 4 ranged between 0.85 and 0.94, which demonstrated support for the use of optimally weighted factor scores as substitutes for latent factors in the structural model (Gorsuch, 1983; Wang & Wang, 2020). The variables in the correlation matrix reported in Table 4 show good discriminate validity as all values below the diagonal are lower than the square root of the average variance extracted (AVE), which is presented on the diagonal (Fornell & Larcker, 1981).

Overall, the factor models for the constructs or variables included in this study showed acceptable psychometric properties and can be considered suitable for use in the structural model.

Table 3. *Model Fit Statistics and Factor Loadings per Unidimensional Factor Model for the Variables Included in the Study* (N = *1,594)*

Factor model - *Subscale/facet*	*N* of Items	$\chi 2$	*CFI*	*TLI*	*SRMR*	*RMSEA*	Factor loadings Range	Mean
a) Study resources	18	568.46**	0.94	0.93	0.04	0.05	0.38-0.67	0.54
- Growth	6							
- Peer support	3							
- Information accessibility	3							
- Lecturer support	6							
b) Physical resources	4	7.98**	0.99	0.98	0.01	0.04	0.58-0.72	0.64
c) Study demands	5	77.28**	0.93	0.86	0.04	0.09	0.38-0.67	0.54
d) Burnout risk[1]	18	1267.3**	0.91	0.9	0.04	0.07	0.34-0.99	0.72
- Personal burnout	6							
- Study-related burnout	6							
- Peer-related burnout	6							
e) Student engagement	24	1140**	0.95	0.94	0.04	0.05	0.68-0.88	0.79
- Emotional engagement	6							
- Physical engagement	6							
- Cognitive engagement in class	6							
- Cognitive engagement outside the classroom	6							
f) Student–LMX	7	128.72**	0.97	0.94	0.04	0.08	0.53-0.84	0.69
g) Deep-learning approach	10	213.68**	0.96	0.95	0.03	0.06	0.44-0.72	0.63
- Deep motive	5							
- Deep strategy	5							
h) Surface-learning approach	10	346.43**	0.91	0.87	0.05	0.08	0.44-0.70	0.54
- Surface motive	5							
- Surface strategy	5							
i) Academic performance	n/a	n/a						

Note: χ2, chi-square statistic*; df,* degrees of freedom*; p, ** p-value* ≤ 0.01*; CFI,* Comparative fit index*; TLI,* Tucker-Lewis index*; SRMR,* Standardised root means square residual*; RMSEA,* Root mean square error of approximation; [1], Second-order model, _, underlined values represent the total number of items included in the factor model.

Table 4. *Intercorrelations and AVE Values for the Variables Used in the Study*

Variables/factor model		a	b	c	d	e	f	g	h	FD	ω	N
a)	Study resources	0.76								0.91	0.84	1594
b)	Physical resources	0.33*	0.65							0.87	0.74	1594
c)	Study demands	-0.25*	-0.22*	0.56						0.85	0.68	1594
d)	Burnout risk	-0.43*	-0.33*	0.39*	0.71					0.95	0.86	1594
e)	Student engagement	0.54*	0.21*	-0.13*	-0.39*	0.80				0.93	0.87	1594
f)	Student–LMX	0.65*	0.23*	-0.22*	-0.33*	0.47*	0.70			0.94	0.87	1594
g)	Deep-learning approach	0.40*	0.13*	-0.06*	-0.33*	0.56*	0.41*	0.63		0.94	0.87	1594
h)	Surface-learning approach	-0.02	-0.08*	0.10*	0.13*	-0.07*	0.01	0.19*	0.55	0.90	0.81	1594
i)	Academic performance	0.10*	0.11*	-0.06	-0.04	0.08*	0.15*	0.03	-0.03	NA	NA	853

Note: N, study sample*; FD,* Factor score determinacy*; ω,* McDonald's omega*;* _, underlined values on the diagonal represent the square root of the AVE (Fornell & Larcker, 1981); *, statistically significant *(p* ≤ 0.05*).*

Testing the Path/Structural Models

A summary of all hypotheses formulated and tested in this study is presented in Table 5

Testing of Model 1

The hypothesised Model 1 (see Figure 1) provided a poor fit to the data ($\chi2$ [35, *N* = 853] = 350.05, *p* = 0.00; *CFI* = 0.69; *SRMR* = 0.10; *TLI* = 0.55; *RMSEA* = 0.10) and casted doubt over the trustworthiness of the regression paths. As reported earlier, the results of academic performance showed 46% missing cases due to students indicating incorrect module codes. The reduced sample size (*N* = 853) for Model 1 was considered less representative of the student population and less suitable for the SEM analysis. However, the pruning of insignificant regression paths can enhance the overall model fit and parsimony (Streiner, 2005). According to Streiner (2005), variables that do not relate to other variables in the model should be considered for exclusion. The correlation matrix in Table 4 showed that academic performance showed small correlations ($r < 0.15$) with all other variables in the model and would likely not result in contributory regression paths. Accordingly, the estimates for H6, H8a, and H8b for Model 1 were all insignificant (H6: $\beta = 0.08$, $p = 0.07$; H8a: $\beta = -0.01$, $p = 0.75$; H8b: $\beta = -0.02$, $p = 0.62$) and non-contributory paths in the model. As some doubt existed about the trustworthiness of these estimates, H6, H8a, and H8b were tested in a separate regression analysis that included only the relevant variables. Student engagement, deep-learning approach, and surface-learning approach were regressed on academic performance. The results of the regression analysis precisely replicated the estimates reported in Model 1 for H6, H8a, and H8b and the hypotheses were consequently rejected. The total variance explained for the regression model was 1% and statistically insignificant ($R^2 = 0.01$, $p = 0.26$). We decided to reject Model 1 and exclude academic performance from further analyses.

Testing of Modified Model 2 (Excludes Hypotheses H6, H8a, H8b Pertaining to Academic Performance)

Taking prior empirical work into consideration, alternative models were tested using the total sample (*N* = 1,594) which can be considered more suitable for the SEM analysis and more representative of the student population. Model 2 was based on Model 1's template but excluded academic performance as an endogenous variable and allowed the deep-learning and surface-learning approaches to covary. It was found that Model 2 showed a slightly better but inadequate fit ($\chi2$ [25, *N* = 1590] = 410.40, *p* = 0.00; CFI = 0.77; SRMR = 0.10; TLI = 0.65; RMSEA = 0.10). The model was consequently rejected as it was not supported by the data.

Testing of Modified Model 3 (See Figure 2, Exploratory Hypothesis H10, H11, and H12 Were Added)

Next, a modified model Model 3, which included additional regression paths was tested. Exploratory hypotheses, supported by theory and data, were used to justify the inclusion of additional paths in the model (Hollenbeck & Wright, 2017). The residuals of the covariance matrix were used to identify additional paths that would improve the overall model fit. Only the paths that were justified by theory and related empirical studies were added. In this modified model, burnout risk and deep-learning approach as dependent variables were regressed on study resources, which represent the two post hoc hypotheses, Hypothesis 10 and Hypothesis 11, respectively. More specifically the hypotheses stated:

H10: There is a statistically significant positive relationship between study resources and a deep approach to learning.

H11: There is a statistically significant negative relationship between study resources and burnout risk.

A surface-learning approach as the dependent variable was regressed on burnout risk and represent post hoc Hypothesis 12 (H12). The hypothesis stated:

H12: There is a statistically significant positive relationship between burnout risk and a surface approach to learning.

Support for hypothesis H10, H11, and H12 were found in studies by Mokgele and Rothmann (2014), Fourie (2003), and West and Halvorson (2019). Mokgele and Rothmann (2014) found that both study demands and a lack of resources were associated with burnout, potentially resulting in first-year students being unable to achieve their study goals. Further, to minimise the negative impact of burnout, students may reduce discretionary inputs. Mokgele and Rothmann further noted that burnout results in a loss of motivation. Deep learning takes place when students have the intrinsically motivated intention to understand the meaning of their work, whereas surface learning occurs when students take a passive stance (Fourie, 2003; West & Halvorson, 2019).

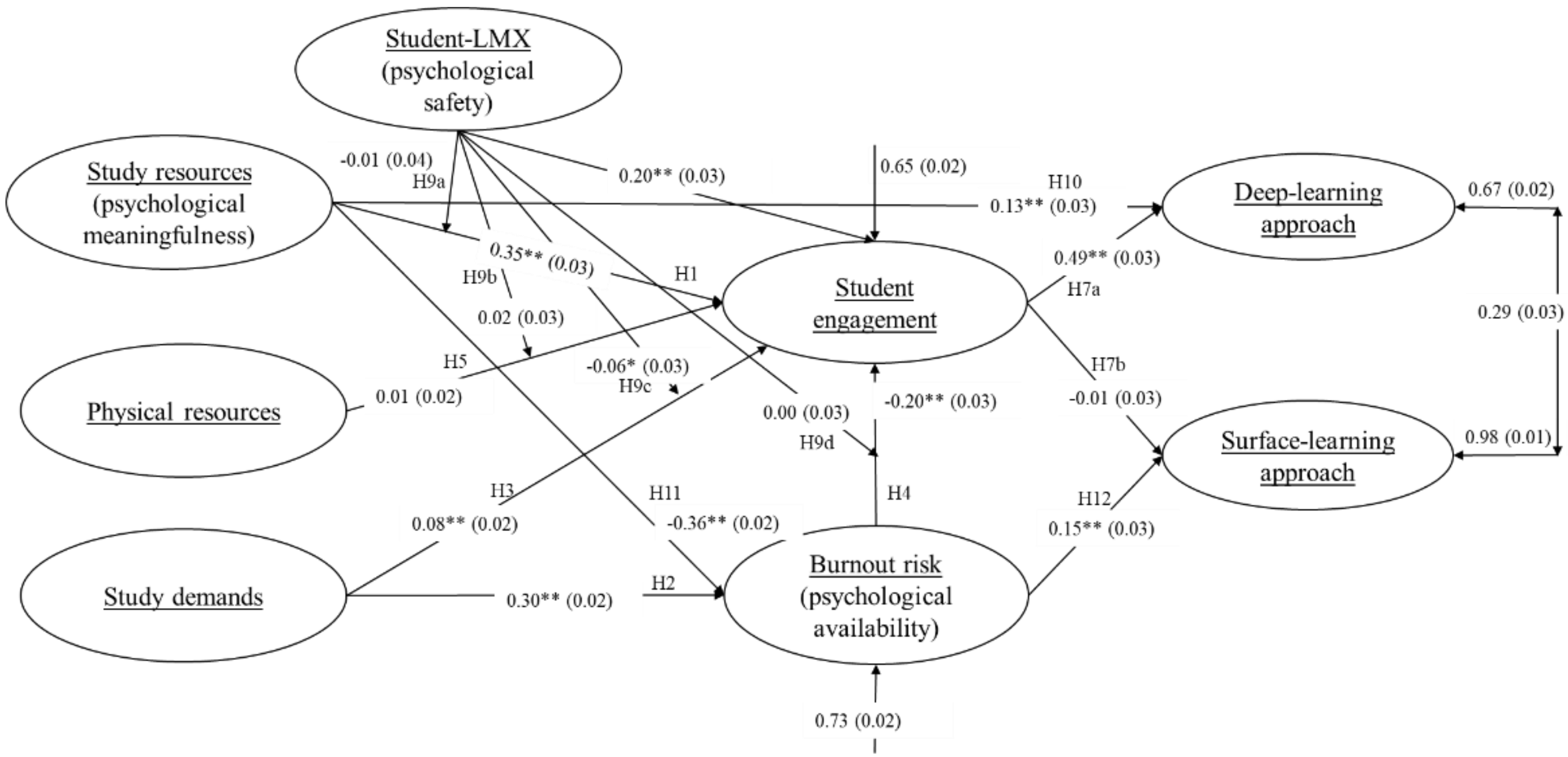
The modified model produced significantly improved model fit ($\chi2$ [22, N = 1,594] = 157.52, p = 0.00; *CFI* = 0.92; *SRMR* = 0.04; *TLI* = 0.86; *RMSEA* = 0.06) and, therefore, formed the basis of the structural model. It should be noted, however, that this model might not be generalisable to other samples and would require further confirmatory studies. Results as per hypothesis formulated for this study are presented in Table 5 and Model 3 is presented in Figure 2.

Table 5. *Results as per Hypotheses Set in the Study*

	Hypothesis	β estimates	Result
H1	There is a statistically significant positive relationship between study resources and student engagement.	0.35**	Supported
H2	There is a statistically significant positive relationship between study demands and burnout risk.	0.30**	Supported
H3	There is a statistically significant negative relationship between study demands and student engagement.	0.08**	Supported
H4	There is a statistically significant negative relationship between burnout risk and student engagement.	-0.20**	Supported
H5	There is a statistically significant positive relationship between physical resources, such as adequate study conditions at home, access to a stable internet, electricity, and devices, and student engagement.	0.01	Not supported
H6	There is a statistically significant positive relationship between student engagement and academic performance.	0.08	Not supported
H7a	There is a statistically significant positive relationship between student engagement and a deep-learning approach	0.49**	Supported
H7b	There is a statistically significant negative relationship between student engagement and a surface-learning approach.	-0.01	Not supported
H8a	There is a statistically significant positive relationship between a deep approach to learning and academic performance.	-0.01	Not upported
H8b	There is a statistically significant negative relationship between a surface approach to learning and academic performance.	-0.02	Not supported
H9a	Student–LMX, which carries aspects of psychological safety, moderates the relationship between study resources (meaningfulness) and engagement, such that high student–LMX strengthens the positive relationship between study resources and student engagement.	-0.01	Not supported
H9b	Student–LMX moderates the relationship between physical resources and student engagement, such that high student–LMX strengthens the positive relationship between adequate physical resources and student engagement.	0.02	Not supported
H9c	Student–LMX moderates the relationship between study demands and student engagement, such that high student–LMX acts as a buffer against the negative effect of study demands on student engagement.	-0.06*	Supported
H9d	Student–LMX moderates the relationship between burnout risk (availability) and student engagement, such that burnout risk is less (vs. more) negatively related to student engagement at high student–LMX levels.	0.00	Not supported
H10	There is a statistically significant positive relationship between study resources and a deep approach to learning.	0.13**	Supported
H11	There is a statistically significant negative relationship between study resources and burnout risk.	-0.36**	Supported
H12	There is a statistically significant positive relationship between burnout risk and a surface approach to learning.	0.15**	Supported

Note: ** $p \leq 0.01$; * $p \leq 0.05$.

Figure 2. The Final Path/Structural Model (Model 3)



Note: ** *p* < 0.01; * *p* < 0.05; LMX, leader-member exchange

Discussion

In this section, we discuss the results of the study in relation to the study purpose and the findings in existing literature. The primary objective of this study was to explore the interplay of psychological conditions that influenced engagement (Kahn, 1990) among university students. This study further aimed to explore student learning approaches by extrapolating from findings reported in work done on the JD-R model (Bakker & Demerouti, 2017) to extend the existing understanding of how student engagement influenced learning approaches, which represented student intention to learn and the learning processes students followed (Campbell & Cabrera, 2014).

The Relationships Between Study Resources, Physical Resources, Study Demands, Burnout Risk, Student-LMX, and Student Engagement

Previous empirical studies within an education context have established that predictors of student engagement include study resources (Bakker et al., 2015; Mokgele & Rothmann, 2014; Robins et al., 2015), study demands (Cilliers et al., 2018; Robins et al., 2015), student–LMX (Farr-Wharton et al., 2018), and burnout (Salmela-Aro & Upadyaya, 2014; Singh et al., 2020), among other antecedents. To explore the psychological conditions that led to engagement, this study established connections between Kahn's (1990) theory on engagement, the SD-R model, and LMX theory to operationalise study resources, burnout risk, and student–LMX as the psychological conditions of meaningfulness, availability, and safety.

Results showed that study resources (meaningfulness), burnout risk (availability), student–LMX (safety), and study demands, accounted for 35% of the variance in student engagement. These results provided support for operationalising study resources, burnout risk, and student–LMX as psychological conditions and extrapolating Kahn's (1990) theory beyond the employer/employee context to the student environment. The results show that study resources (psychological meaningfulness) seemed of greater importance in explaining student engagement, as it showed a stronger association with engagement than did burnout risk, student–LMX, and study demands. This strong association of study resources with student engagement aligns with the SD-R model (Mokgele & Rothmann, 2014). In addition to establishing that the three psychological conditions influenced student engagement, in contrast to Hypothesis 3, we found a positive association between study demands and engagement. Although the effect of this association was very small, the finding that study demands were positively associated with student engagement was nonetheless unexpected as it contradicted findings from existing empirical work (Cilliers et al., 2018; Robins et al., 2015). Crawford et al. (2010) made a distinction between demands that hinder and those that challenge, stating that challenging demands are regarded as activities that may lead to individual growth or personal gain, thus triggering strategies such as putting in more effort. The COVID-19 pandemic brought about changes such as the interruption of educational activities and the extension of the academic year. It may be surmised that these circumstances created the opportunity for students to view study demands (e.g., time pressure, perceptions of having to work extra hard) (SD-R scale, Mokgele & Rothmann, 2014) as challenging demands that, if met, would lead to personal gain (e.g., the completion of their study year).

To test the coaction of the psychological conditions on engagement, the moderating relationship of student–LMX (safety) was included in the hypotheses. None of these moderating effects as postulated in the hypotheses were significant. The findings of De Moura et al. (2020) in their recent study may provide insight into the findings of the present study. These authors stated that extreme circumstances (e.g., a crisis such as COVID-19) may create an adverse environment for line managers to exert an influence over subordinates and that high-quality exchange relationships with line managers may no longer have the capability to, for example, buffer psychosocial stress at work. Similarly, in the context of student-lecturer relationships, a highly supportive student–LMX environment might not have the same influence in times of crisis as it would have had in normal circumstances.

Even though previous studies pointed toward the importance of physical resources in engaging students (Tigaa & Sonawane, 2020), especially during the period of COVID-19, findings from the present study indicated that the physical resources students had available did not influence their engagement. This might be due to an increase in support from the university during COVID-19, such as providing students laptops and/or zero-rated data to ensure a continuation of academic activities. Recent studies have indicated that universities' efforts to manage the negative impact of the COVID-19 lockdown on students have resulted in more students taking the view that they have the required resources available for their studies (Van Zyl et al., 2021).

The Relationships Between Study Demands, Study Resources, and Student Burnout Risk

In alignment with previous studies (Mokgele & Rothmann, 2014; Robins et al., 2015), the present study found that both study demands and study resources were associated with burnout risk and explained 27% of the variance in burnout risk. Contrary to expectations proposed in the JD-R model that demands would be most important in explaining burnout risk, study resources showed a stronger association with burnout risk than did study demands. This aligns with findings by Mokgele and Rothmann (2014), who found that the effect of study resources on burnout risk was twice as strong as that of study demands. It should be noted that study demands other than those considered in the present study could be important in explaining student burnout risk.

The Relationships Between Student Resources, Student Engagement, Burnout Risk, and Deep and Surface Approaches to Learning

Student engagement and student resources predicted 33% of the variance in a deep approach to learning, with engagement showing a medium positive effect, whereas the effect of study resources was regarded as small. This finding supported the findings of Floyd et al. (2009) and Bevan et al. (2014) that student engagement had a significant effect on student deep-learning approach. In addition, Platow et al. (2013) suggested (but did not confirm by way of a test) that the actual time and resources students have available could influence whether they engage in a deep-learning approach.

The results further indicated that burnout risk only explained a very small percentage (2%) of the variance in a surface-learning approach, whilst engagement had no association with surface learning. In a surface-learning approach, students choose to rely on memory rather than on comprehension, and their motivation or desire is to exert minimal effort in completing study tasks (Aharony, 2006). Mokgele and Rothmann (2014) posited that students may lose motivation and reduce discretionary inputs due to the negative effects of burnout. It did seem, however, that factors other than those tested in this study might rather lead to a surface learning approach, and that the view of Kuittinen and Meriläinen (2011) that a surface learning approach may be an inevitable survival strategy for students, might hold some merit. Accordingly, the assumption can be made that all the challenges caused by the COVID-19 pandemic (e.g., dealing with sick family members, adapting to a full or blended online mode of teaching, and dealing with study time pressure) may create the circumstances for students to have the perception that they need to do the bare minimum required to survive the academic year.

Limitations and Recommendations for Future Research

Although the study provided noteworthy insights in terms of extending Kahn's (1990) theory to the student context and connecting this theory with student–LMX and the SD-R model, the study had some limitations. First, as data were obtained from students in one university in one province in South Africa, the generalisation of the study's results was limited. Research that includes other universities in different provinces locally or internationally would be worthwhile to consider in future studies.

Second, because the study used self-report data and a cross-sectional approach, causal inferences could not be made, and the possibility of common method variance existed. An in-depth longitudinal design may aid in gaining a better understanding of the interplay and causal influences among the constructs. Although the study did implement methods to mitigate common method variance, for instance the use of different scale formats and anchors (Podsakoff et al., 2012), we recommend that future studies obtain data using different methods or obtain data from multiple respondents or sources.

A third limitation was related to the inclusion in the measurement model of students' marks in respect to a chosen semester and module as a measure of academic performance. The study relied on students to provide their student number and select a module code from a drop-down list, which included the option "Other" that allowed students to manually input the module code. Unfortunately, some students who chose this option either entered the incorrect module code or the course or module name instead of the module code or no alternative module code or no code number. As a result, the data on academic performance presented significant missing values (46%). Consequently, a poor model fit was obtained for the measurement model, and the measure of academic performance had to be removed from this model and could not be included in testing the structural model. It is further noted that the modified model tested might not be generalisable to other samples and would require further confirmatory studies.

Implications of the Research

Kahn (2014) provided evidence that HE institutions had a lot to gain from fostering student engagement. However, Baron and Corbin (2012) indicated that, although many universities have a plethora of practices, initiatives, and policies in place to increase academic engagement, these are often fragmented, at times contradictory, and lacking in a common understanding of how to gauge engagement. These authors urged institutions to think more carefully and holistically about student engagement, to stop viewing it as a quality control indicator, and to rather see it as a matter that can generate meaningful dialogue. The findings of the present study revealed that Kahn's (1990) conceptualisation that specific conditions lead to engagement within the workplace held true in a student learning environment and that the SD-R model and the student–LMX theory could be used to operationalise these psychological conditions.

During the COVID-19 pandemic, most students experienced feelings of not being in control, of having to put their lives on hold, and of being isolated academically (Visser & Law-Van Wyk, 2021). The knowledge that one's context influences one's perception and one's decision to either engage or not (Kahn, 1990) holds some implications. HE leaders are encouraged to focus efforts not only on ensuring that students perceive the structures and physical resources provided during periods of uncertainty, such as the global COVID-19 pandemic, as adequate, but rather also, holistically consider the conditions that encourage student engagement. These conditions include psychological meaningfulness (study resources), availability (burnout risk), and safety (student–LMX). Although the study's findings highlighted the importance of all these psychological conditions in fostering engagement, meaningfulness, which was operationalised as study resources, showed a stronger association with engagement than did student–LMX (safety), study demands, and burnout risk (availability). These findings suggest that university leaders should give extra attention to providing study resources (growth, peer support, lecturer support, information accessibility) that tap the domain of meaningfulness, to promote student engagement.

Earlier studies indicated that the well-being and future workplace success of young people are dependent on them using their minds well, which they do when they are deeply engaged in learning (Dunleavy & Milton, 2008). West and Halvorson (2019) confirmed that heightened student engagement leads to deep learning. By extrapolating from work done on the JD-R and SD-R models, findings from this study demonstrated that engagement influenced a deep-learning approach and that there was a clear gain in fostering student engagement in terms of achieving outcomes such as a deep-learning approach.

Conclusion

Kahn (1990) illustrated in his grounded theoretical framework on engagement that the psychological experiences of availability, safety, and meaningfulness lie at the foundation of decisions people make to either bring the “self” into a work role through psychological presence and personal engagement or to withdraw. Findings from the present study demonstrated that Kahn’s (1990) theory carried implications beyond the workplace and held true in a student learning environment. Further, an exploration of the psychological conditions that led to engagement showed that the SD-R model could be used to operationalise study resources as psychological meaningfulness and burnout risk as availability. Similarly, in the context of exploring the student–lecturer relationship, student–LMX could be operationalised as psychological safety.

In exploring outcomes (e.g., a deep approach to learning) that supported students in becoming lifelong learners, this study highlighted the important contribution of engagement, and it provided support for using the SD-R model to explore a deep approach to learning in the context of student learning.

Ethics Statement

Ethical approval to conduct the research was obtained from the Faculty of Economic and Management Sciences at the University of Pretoria (Protocol number: EMS105/20).

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