European International University, EIU-Paris

Doctoral Thesis

Title:

Investigating the effects of doctoral students' well-being and their antecedents and consequences from a Job Demands-Resources perspective

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Abstract

The psychological well-being of doctoral students has emerged as a critical concern within the global higher education landscape, with increasing evidence of stress-related challenges and emotional strain. Despite extensive literature on doctoral mental health, limited research has examined the antecedents of well-being and its downstream consequences, particularly in Southeast Asian contexts. This study aims to investigates the relationship between the research environment and doctoral students' psychological well-being, and how well-being influences their intention to quit. The method involved a correlational research design with data from 278 doctoral students collected via an online survey. Structural Equation Modelling (SEM) was conducted using Smart-PLS version 4 to evaluate both measurement and structural models. All four hypotheses were supported. The research environment significantly predicted psychological well-being ($\beta = 0.412$, $t = 5.115$, $p < 0.05$, CI = [0.258, 0.607]), and both well-being ($\beta = 0.448$, $t = 4.096$, $p < 0.05$, CI = [0.239, 0.547]) and the research environment ($\beta = 0.447$, $t = 5.609$, $p < 0.05$, CI = [0.262, 0.587]) were significant predictors of intention to quit. Additionally, psychological well-being mediated the relationship between the research environment and intention to quit ($\beta = 0.185$, $t = 3.242$, $p < 0.05$, CI = [0.091, 0.306]). Key findings include the dimensions of the research environment, supervision, resources, research community, and professional development, were found to be distinct contributors to well-being and attrition risk. The findings offer theoretical insights into the JD-R model's applicability in doctoral education and practical implications for institutional policies aimed at enhancing supervisory support, resource access, and community engagement. This study contributes to a deeper

understanding of how structural and relational aspects of the research environment shape doctoral students' psychological outcomes and retention.

Keywords: Doctoral students, intention to quit, job demands-resources theory, research environment, well-being

Acknowledgments

"If you think education is expensive, try estimating the cost of ignorance."

Howard Gardner

This is my third doctoral dissertation, and I am not done yet. Many of my friends often asked me, "when are you going to stop learning?" My reply to this question is always the same, "the day I stopped learning, it's the day I stopped leading." Every milestone in my learning journey, big or small, has inspired me to continue my quest for new knowledge. Deep within myself, I know that the cost of ignorance far outweighed the cost of education or any other forms of learning in a world like ours today. While this is my third dissertation, it would not have been possible without the guidance, support, and love of some of the most important people in my life. First and foremost, I would like to express my gratitude to the person that has inspired me to continue my journey lifelong learning, Ky. Col. Prof. Dr. Edward Roy Krishnan. His timely guidance and support have helped me through many long and lonely nights like a beacon lighting up the dark waters. As I conclude my doctoral journey, I would like to give a big shoutout to my family for your understanding and encouragement throughout this journey.

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Chapter 1: Introduction

Introduction

Pursuing a doctoral degree can be a stressful endeavor which can lead to some cases of doctoral candidates feeling exhausted and burnout (Hermann, 2021). Based on a study by Evans et al. (2018), there is increasing evidence that graduate students across the world are suffering from significant mental health concerns during their studies. This is illustrated through an international study of more than 2,000 PhD students from across 26 countries which highlighted that 41% and 39% of the PhD students suffer from anxiety and depression respectively, in contrast to 6% of the general population (Evans et al., 2018). Apart from the feeling of anxiety and depressed, several students were suffering from stress and experiencing loneliness (Hermann et al., 2014; Jacobsson & Gillström, 2006). These alarming trends have been cited by other studies in different contexts such as discipline specific, campus, department or university (El-Ghoroury et al., 2012; Gillespie et al., 2001).

Background

In recent years, psychological well-being of doctoral students has attracted extensive international media attention across the higher education sector (Metcalfe et al., 2018; Woolston, 2019). This phenomenon is reflective of the recent evidence that psychological well-being is negatively correlated with depression (Clarke et al., 2011; Zadow et al., 2017). In addition, several studies have highlighted the presence of significant relationship between psychological well-being and perceived stress, resilience,

mindfulness, perceived self-efficacy, and social support among university students (Green et al., 2012; Peng et al., 2012; Roberts et al., 2011; Schoormans & Nyklíček, 2011). There is a lack of consensus in the definition of the term well-being among the doctoral education literature (Schmidt & Hansson, 2018). For this study, psychological well-being was defined as a broad construct involving positive indicators such as happiness, positive functioning, or functioning well psychologically and socially, and the absence of negative indicators such as negative emotionality, and psychopathological sequelae (Houben et al., 2015). Well-being is a multifaceted concept that has been studied in a few different disciplines resulting in different theoretical perspectives focusing on varying levels of emphasize on hedonic (e.g., affective) and eudaemonic (e.g., human functioning) aspects of well-being (Aiello & Tesi, 2017; Deci & Ryan, 2008; Kimbu et al., 2023). Well-being has been traditionally interpreted as residing within the individual; however, it is important to acknowledge that the environment has a role to play in advancing or hindering well-being. Stubb et al. (2011) proposed the argument that 'ill-being is not simply an individual symptom, but a mismatch in the relationship between the individual and the environment'. Jackman and Sisson (2022) highlighted that one of the most critical determinants of PhD students' well-being is the research environment. The study into doctoral students' well-being was extensively researched in the Western society (Castro Silva et al., 2022; Cornér & Pyhältö, 2019; Eversmeyer, 2024; Farewell et al., 2022; Hish et al., 2019; Hlado & Harvankova, 2024; Jansen in de Wal et al., 2017; Kiremitci et al., 2023; Kulikowski et al., 2019; Lep et al., 2023; Nori et al., 2025; Ostermeier et al., 2023; Sorrel et al., 2020; Ueno et al., 2024). However, in recent years, the interest in the research of Job Demands-Resources model

applied as the theoretical framework on doctoral students' well-being is increasing especially in the Asia region. Thus, it is timely to "jump on the bandwagon" by apply the Job Demands-Resources model to investigate the aspects of research environment as antecedents of doctoral students' well-being and the downstream impact on doctoral students' intentions to quit.

Problem Statement

While there is an abundance of empirical studies showing that doctoral students suffer from immense emotional or stress-related issues, yet there is much to investigate about the underlying causes of well-being and their downstream consequences on the young scholars. Majority of these studies were conducted in the Western societies, and there is a lack of scholarship on doctoral student well-being in Southeast Asian societies. Excluding the lack of literature, high supervision workload of more than five full-time doctoral students concurrently (Molassiotis et al., 2020), varied funding mechanisms even within the same region (Shin et al., 2018), and cultural differences in attitudes and perception towards seeking help (Valuyeetham, 2022). Henceforth, this study seeks to address the gaps by investigating doctoral students' well-being, specifically its antecedents (e.g., research environment) and consequences (e.g., intentions to quit). This study leverage on the Job Demands-Resources (JD-R) model as the overarching theoretical framework for this research.

Objectives of Study

This study aims to investigate the aspects of the research environment as antecedents of doctoral students' well-being and their downstream impact on doctoral students' intentions to quit using the Job Demands-Resources model.

Research Questions & Hypotheses

Research questions are important for the researcher to focus on the process and reach the main objective. Specific and well-developed research questions assisted the researcher in working towards the research outcomes. To address the objective of investigating the research environment as antecedents of doctoral students' well-being and their downstream impact on doctoral students' intentions to quit. The research will attempt to address the following questions and associated hypotheses:

1. To investigate the impact of research environment as antecedents on doctoral students' well-being.

H1: The quality of the research environment positively predicts doctoral students' psychological well-being.

2. To examine the downstream impact of doctoral students' well-being on their intentions to quit.

H2: Doctoral students' psychological well-being negatively predicts their intentions to quit.

3. To analyze the mediating role of doctoral students' well-being between the research environment and doctoral students' intentions to quit.

H3: Psychological well-being mediates the effects of the quality of research environment on doctoral students' intentions to quit.

H4: The quality of research environment negatively predicts doctoral students' intentions to quit.

An online questionnaire was administered to students who are currently pursuing their doctoral degrees. The questionnaire items had specific scale labels, and the Likert

scale was assigned to the items. Inferential statistical analysis using Structural Equation Modelling (SEM) was deployed to analyze the quantitative data to establish the reliability and validity of the construct which is fundamental to the assessment of the conceptual model.

Conceptual Framework for the Study

The Job Demands-Resources (JD-R) model was adopted as theoretical framework to investigate the relationship between the research environment, doctoral students' well-being, and consequence on intentions to quit (Kulikowski et al., 2019; Park et al., 2021). The Job Demands-Resources (JD-R) model was first introduced by Bakker, Demerouti, and Euwema (2005) as the model to investigate the risk factors for burnout and its undesirable impact on job demands. Since then, the Job Demands-Resources (JD-R) model has become one of the most widely cited theories for understanding well-being and performance in organizational settings (Bakker & Demerouti, 2017). The two constructs of Job Demands-Resources (JD-R) model namely job demands, and job resources are defined as different aspects of the research environment. Job demands are defined as those physical, psychological, social or organizational aspects of the job that require physiological and/or psychological effort, e.g., heavy workloads, tight deadlines, and rigorous requirements faced by doctoral students (Demerouti et al., 2001). On the other hand, job resources refer to those physical, psychological, social, or organizational aspects of the job that are functional in accomplishing work goals or reduce job demands or promote personal growth, learning, and development (Bakker, 2011; Bakker & Demerouti, 2007).

Definitions of Terms

The definitions of the terms used in this study are as follows:

1. Job demands: "…those physical, psychological, social, or organizational aspects of the job that require sustained physical and/or psychological effort and are therefore associated with certain physiological and/or psychological costs" (Edgerton et al., 2024).

2. Job resources: "…those physical, psychological, social, or organizational aspects of the job that are: (a) functioning in achieving work goals; (b) reduce job demands and the associate physiological and psychological costs; or (c) stimulate personal growth, learning, and development" (Edgerton et al., 2024).

3. Job Demands-Resources model: Work environment or job characteristics can be interpreted along two dimensions: job demands and job resources (Bakker & Demerouti, 2014).

4. Psychological well-being: Psychological well-being was defined as a broad construct involving positive indicators such as happiness, positive functioning, or functioning well psychologically and socially, and the absence of negative indicators such as negative emotionality, and psychopathological sequelae (Houben et al., 2015).

5. Structural equation modelling: Structural equation modelling is a multivariate data analysis method for analyzing complex relationships among constructs and indicators (Hair et al., 2021).

6. Doctoral education: An advanced research qualification, resulting from advanced study and original research typically offered by research-oriented universities, in both academic and professional fields (Sarrico, 2022).

Assumptions

The first assumption associated with this study is the appropriateness of the questionnaire items in delivering the message accurately and the respondents were able to comprehend the questionnaire items correctly. The second assumption was that all the participants of this study responded truthfully to the questionnaire.

Scope and Delimitations

Delimitation is often referred to as the scope or the boundaries of the study. The study adopted the non-experimental research design therefore the generalization of findings must be dealt with caution. In a similar light, the questionnaire deployed for this study was self-reported measures that hinged on the respondents' ability and willingness to report factually.

Significance of Study

This study aims to unravel the complex and intertwined relationship between the variable of research environment as antecedent of doctoral students' well-being and the downstream complications on doctoral students' intentions to quit. Furthermore, this study aims to contribute to the growing body of literature in doctoral education literature. The review of literature also informed that majority of the studies were focused on understanding the negative aspects of well-being and emphasized less on its positive aspects (Jackman & Sisson, 2022). Therefore, the findings of this study inform whether and how well-being would predict doctoral students' intentions to quit.

Chapter Summary

This chapter established the basis for the study by investigating doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources

perspectives. The foundation for this study, namely background of the study, problem statement, assumptions, scope and delimitations and significance of study, were also discussed in detail. The next chapter delves into the review of relevant literature on the Job Demands-Resources (JD-R) model, specifically the research environment as antecedents and the corresponding downstream impact on doctoral students' intentions to quit.

Organization of Dissertation

This dissertation consists of six chapters; with chapter one concluded comprehensively in the earlier section. Chapter two delves into the analysis of relevant literature covering the proliferation of doctoral student well-being, as well as articles with the application of Job Demands-Resources (JD-R) model in the higher education context. Chapter three describes the research methodology that was employed for this study which includes the selection of target population, sample size and the survey instrument, as well as ethical considerations. Chapter four focuses on the discussion of data analysis processes as well as the results which include hypothesis testing and inferential statistical analysis. Chapter five presents the discussion of the findings relative to the developed hypotheses for the study. Chapter six details the conclusion for the study as well as recommendations for future studies.

Chapter 2: Literature Review

Introduction

The objective of this study was to investigate doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources perspectives. This chapter presents a holistic review of literature pertinent to the antecedents and consequences of doctoral students' well-being. The Job Demands-Resources (JD-R) model, by Bakker, Demerouti, and Euwema (2005), is one of the most widely cited theories for understanding well-being and performance in organizational settings. The literature review undergone a rigorous analysis of peer-reviewed scholarly articles on the well-being of doctoral students focusing on research environment as antecedents and how it impacts doctoral students' intentions to quit.

The chapter begins with an elaboration of the literature search strategy to scan for peer-reviewed scholarly articles. The next section establishes the analytical perspective of key constructs in this study, including doctoral students' well-being, the Job Demands-Resources (JD-R) model etc. The third section is an inquiry into the relevant literature on the key constructs. The discussion of the literature review results, and the critique of past research studies are encompassed in the fourth section. The final section encapsulates the insights distilled from the relevant literature.

Literature Search Strategy

The literature search strategy was formulated with the author-led approach as the basis coupled with the guidelines and protocol of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRIMA) advocated by Moher et al. (2010) to reinforce the strategy. The first step begins with the author identifying the key constructs

relevant to the research, like research environment, doctoral students' well-being, Mobley's intentions to quit and the Job Demands-Resources (JD-R) model etc. With the identified constructs, the author proceeds to search the relevant literature through the five selected databases, e.g., Academic Search, CiteSeer^{X}, Google Scholar, Social Science Research Network (SSRN), Educational Resource Information Center (ERIC) using relevant keywords. The search terms consist of permutations of relevant keywords on doctoral well-being, the Job Demands-Resources (JD-R) model, research environment, and intentions to quit. The third step of the strategy is to screen the selected literature, followed by step four to analyze the literature and finally to communicate the findings. Step three to five will be scaffolded in the subsequent sections of the chapter.

The Job Demands-Resources Theory

Since inception, the Job Demands-Resources (JD-R) theory has become one of the most widely cited theories for understanding well-being and performance in organizational settings (Bakker & Demerouti, 2017). For this study, it connects job demands and resources to well-being and performance outcomes in a process model. Though the genesis of Job Demands-Resources theory was developed in the work environment context, the application in doctoral students' research environment has been successful. In a study by Park et al. (2021), the Job Demands-Resources theory was used to examine the effect of job demands and resources on doctoral students' burnout and psychological distress. It was discovered that there is an increased financial strain, lower social support, and a decreased sense of community contribute to the increasing level of burnout. Bakker and Demerouti (2017) described different aspects of the research environment as demands and resources from doctoral students' perspectives. Job

demands are task-related requirements associated with psychological and/or physiological costs. Heavy workloads, tight deadlines, and rigorous requirements are job demands faced by doctoral students. On the other hand, job resources enable conditions that could help doctoral students achieve work goals, stimulate personal growth, and promote learning. An example of job resources is like having a supportive supervisor and intellectually stimulating research climate. Up to now, several studies have focused on possible combination of job demands and job resources and the reported statistical interactions (Bakker et al., 2005, 2007; Hakanen et al., 2005; Xanthopoulou, Bakker, Dollard, et al., 2007). The Job Demands-Resources theory highlights that decreasing job demands and increasing job resources are key in improving well-being (Kulikowski et al., 2019). Furthermore, job resources can buffer the impact of job demands on negative well-being (Bakker & Demerouti, 2017).

Of the 18 reviewed articles, four were published before the year 2020, while the remaining 15 were published after 2020, reflecting a growing interest in the field and possibly an increasing application of Job Demands-Resources model in the education industry. Majority of the articles (12) were centered around the application of Job Demands-Resources model on doctoral students. While these 12 studies reinforced the robustness of the Job Demands-Resources model in education, it requires cautious extrapolation to doctoral contexts. Amongst these 12 studies, three specific studies focused on the resource dimension of the Job Demands-Resources model and highlighted the importance of individual and social buffers against stress. The remaining seven articles were also in the field of education but focusing on other stakeholders such as teachers, faculty and staff of an educational institution. Data for 11 of the 19 studies were

collected from a pan-European mix consisting of Czech Republic, Finland, Netherlands, Poland, Slovenia, Spain, UK. These 11 studies directly examine psychological well-being and validate the need for institutional support and resource access. Another three had data from USA, while the remaining five studies came from Asia consisting of China and India. Studies by Acharya et al. (2024), Cornér and Pyhältö (2019), Li et al. (2025) directly explore the construct, research environment, specifically supervision and institutional climate. It is evident that the Job Demands-Resources model was extensively researched in the Western society. Notably, in the recent years, there is a growing interest in the research of Job Demands-Resources model applied on doctoral students' well-being in the Asia region. Therefore, the intent of this study is to focus on the application of Job Demands-Resources model to investigate the impact on doctoral students' well-being. It aims to investigate the effects of resource aspects of research environment on impacting psychological well-being of doctoral students. The complete list of literature reviews is summarized in Table 1.

Table 1

Summary of Literature Review

Authors/year	Title	Country	Sample	Design
1. Jansen in de Wal et al. (2017)	The relationship between job demands, job resources and teachers' professional learning: is it explained by self-determination theory?	Netherlands	T1: 678 secondary teachers T2: 536 secondary school teachers	Quantitative
2. Cornér and Pyhältö (2019)	Supervisors' Perceptions of Primary Resources	Finland	15 semi-structured interviews	Qualitative

	and Challenges of the Doctoral Journey		with professors	
3. Kulikowski et al. (2019)	How to Survive in Academia: Demands, Resources and Study Satisfaction Among Polish PhD Students	Poland	360 PhD students	Quantitative
4. Hish et al. (2019)	Applying the Stress Process Model to Stress–Burnout and Stress–Depression Relationships in Biomedical Doctoral Students: A Cross-Sectional Pilot Study	USA	69 Doctoral students	Quantitative
5. Sorrel et al. (2020)	It must have been burnout: Prevalence and related factors among Spanish PhD students	Spain	305 PhD students	Quantitative
6. Castro Silva et al. (2022)	Job demands and resources as predictors of well-being in portuguese teachers	Portugal	319 Portuguese teachers	Quantitative
7. Farewell et al. (2022)	Job Demands and Resources Experienced by the Early Childhood Education Workforce Serving High-Need Populations	USA	137 ECE staff	Quantitative
8. Liu et al. (2023)	The influence of challenge research stressors on research creativity among Chinese doctoral	China	538 Doctoral students	Quantitative

	students: a mediated moderation model			
9. Ostermeier et al. (2023)	Effects of job demands and resources on thesubjective well-being of teachers	UK	954 teachers	Quantitative
10. Lep et al. (2023)	The relative effect of job demands, resources, and personal resources on teaching quality and students' engagement during the COVID-19 pandemic	Slovenia	1422 8th grade teachers	Quantitative
11. Kiremitci et al. (2023)	Job demands-resources model and burnout in physical education teaching: A mixed-method sequential explanatory study	Finland	I: 173 teachers II: 14 teachers	Quantitative/ qualitative
12. Hlado and Harvankova (2024)	Teachers' perceived work ability: a qualitative exploration using the Job Demands-Resources model	Czech Republic	14 upper secondary school teachers	Qualitative
13. Ueno et al. (2024)	Job demands-resources theory extended: stress, loneliness, and care responsibilities impacting UK doctoral students' and academics' mental health	UK	Secondary dataset of 4,563 academic researchers	Quantitative

14. Eversmeyer (2024)	Social and Organizational Predictors of Burnout Among Health Service Psychology Doctoral Students: An Application of the Job Demands-Resources Model	USA	268 Doctoral students	Quantitative
15. Cao et al. (2024)	Who matters and why? The contributions of different sources of social support to doctoral students' academic engagement	China	472 Doctoral students	Quantitative
16. Acharya et al. (2024)	Institutional, supervisory, and personal demands: unravelling the challenge-hindrance demands in doctoral programs	India	35 semi-structured interviews with PhD students	Qualitative
17. Cao et al. (2024)	Subjective well-being among PhD students in mainland China: the roles of psychological capital and academic engagement	China	376 PhD students	Quantitative
18. Nori et al. (2025)	Fitting in or burning out? Doctoral students' motivations, resources, and the demands of academic work	Finland	1,694 Doctoral students	Quantitative
19. Li et al. (2025)	Igniting doctoral students' work engagement: the roles	China	355 Doctoral students	Quantitative

	of managing up atmosphere and work passion within their research groups from a job demands-resources perspective

Source: Author's calculations using primary data.

The Conservation of Resources (COR) Theory

COR Theory, developed by Hobfoll in 1989, is a foundational framework for understanding stress. It posits that stress primarily arises from the loss of significant resources, while acquiring resources serves as a protective factor against psychological strain. This theory has deeply influenced the understanding of burnout, particularly in high-demand environments where cognitive, emotional, and social resources are frequently strained (Hobfoll, 2001; Hobfoll et al., 2018). COR Theory is one of the most empirically validated frameworks in occupational stress research, providing predictive strength across various work settings (Halbesleben et al., 2014; Hobfoll et al., 2018).

COR theory builds upon earlier models, including the Job Demands-Control-Support (JDCS) Model, which was initially introduced by Karasek in 1979 and later expanded by Karasek and Theorell in 1990. While the JDCS Model emphasizes job demands, autonomy, and social support in relation to job strain, COR Theory shifts the focus to the processes of resource acquisition, loss, and protection. The integration of these theories offers a more comprehensive framework for explaining chronic stress and burnout, particularly in dynamic and evolving work environments (Grandey & Cropanzano, 1999; Halbesleben et al., 2014; Hobfoll, 2001). Unlike the JDCS or Transactional Stress Model, which explains strain primarily through demand-control

balance or appraisal, COR Theory directly addresses how prolonged exposure to resource-threatening environments contributes to burnout trajectories.

A key concept within COR Theory is the "primacy of resource loss," which states that the adverse effects of losing resources far outweigh the positive effects of gaining them (Hobfoll, 2001). This principle helps explain the potential for burnout to escalate, as initial depletion increases individuals' vulnerability to further losses. COR Theory also highlights the importance of resource investment and recovery, noting that resource gains can help offset or buffer the impact of earlier resource losses (Hobfoll, 2001; Hobfoll et al., 2018). Individuals or workplaces that possess one type of resource, such as autonomy, often have access to others, like social support. These combinations of resources can collectively act as a buffer against burnout (Hobfoll, 2001; Hobfoll et al., 2018). These principles emphasize the importance of maintaining access to a diverse range of overlapping resources to prevent burnout and support sustained functioning in complex occupational environments.

The Job Demands–Resources (JD-R) model and the Conservation of Resources (COR) theory both provide influential frameworks for understanding stress, motivation, and performance, yet they diverge in scope, unit of analysis, and explanatory emphasis. While they share a common concern with the role of resources in shaping individual and organizational outcomes, their theoretical architecture and empirical applications reveal important distinctions that must be acknowledged in any integrative review. The JD-R model emerged as a flexible, work-specific heuristic designed to classify job characteristics into two overarching categories: demands and resources. Job demands are defined as aspects of work that require sustained physical or psychological effort and are

therefore associated with physiological and psychological costs. In contrast, job resources are those aspects of work that facilitate goal attainment, reduce the impact of demands, and stimulate personal growth and development. By contrast, COR theory adopts a broader and more general stress perspective, extending beyond the occupational domain to encompass diverse life contexts. COR theory is predicated on the principle that individuals strive to obtain, retain, and protect valued resources, which may include objects, conditions, personal characteristics, and energies. A central tenet of COR is the primacy of resource loss, which asserts that losses are more salient and impactful than gains. Moreover, COR introduces the notion of loss and gain spirals, whereby initial losses can precipitate further depletion, while resource gains can accumulate to create resilience.

Definition of Well-Being

Since the 1980s, well-being has been a multifaceted phenomenon that has been defined in various ways across different disciplines. It was also described as a “catch-all category” (Cameron et al., 2006) that has yet to reach a consensus in the definition (Seedhouse, 1995). According to the World Health Organization, “health” is commonly associated in defining well-being by extension of its definition that “Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity” (World Health Organization, 1948). On the other hand, Larson (1999) has argued that the definition of health was unclear leading to occasional criticism. Galvin and Todres (2011) also acknowledged that well-being is more complex than health and is not limited to any setting or role, e.g., workplace well-being or the role of being a student. Thus, their definition focuses on the essence of well-being. For the purpose of

this study, the focus of well-being lies in the role of the doctoral student, and it would be operationalized in the next section.

Doctoral Students' Well-Being

Conceição et al. (2019) characterized doctoral study as a strict, independent, lonely and isolating journey. Over the last two decades, the emergence of two dominating perspectives of well-being: (1) psychological (or eudaimonic) well-being; and (2) subjective (or hedonic) well-being (Biswas-Diener, 2018; Ryan & Deci, 2001; Ryff & Keyes, 1995). Both perspectives overlap though originated from different philosophical views (Lundqvist, 2011). From the eudaimonic perspective, psychological well-being is interpreted as an ideal state of individual psychological functioning which results in an overall greater sense of satisfaction with life and that better enables the achievement of individual goals (Aiello & Tesi, 2017). As mentioned previously, well-being can be perceived as a broad construct which involves positive indicators such as happiness, positive functioning and the absence of negative indicators such as depression and illness (Keyes & Lopez, 2009). In the doctoral education literature, many studies have focused on indicators of negative well-being, such as stress (Byrom et al., 2022), depression (Levecque et al., 2017), and burnout (Kusurkar et al., 2022). Jackman and Sission (2022) highlighted that the literature primarily focused on understanding negative aspects of well-being and less emphasis on its positive aspects. Though acknowledging the signs of negative well-being is important, it is equally valuable to explore what promotes psychological well-being among doctoral students (Jackman & Sisson, 2022). Therefore, this study operationalizes doctoral students' well-being in terms of psychological well-being (e.g., positive functioning in individual life).

Research Environment

For doctoral students, the research environment is one of the most important organizational contexts in that it is an important enable or, conversely, a barrier to optimal well-being (Levecque et al., 2017). The postgraduate research experience survey is a biennial survey designed to collect feedback from postgraduate researchers about their experiences of their programme and their development as researchers (Neves, 2018). Many existing studies have mostly focused on merely one or two aspects of the research environments (Sverdlik et al., 2018; Lonka et al., 2019; Al Makhamreh et al., 2020; Levecque et al., 2017). The original postgraduate research experience survey consists of seven dimensions relating to research environments. These dimensions include: supervision (the relationship a student has with their supervisor; the availability of a supervisor in providing the student with adequate feedback and guidance); resources (computing amenities' access to students, high-quality books and journals, library facilities, and support financially); research community (the department's intellectual surroundings, that include opportunities for experiencing social interactions, partaking in research ventures, motivating seminars); progress and assessment (clarity of standards and requirements so that an individual can fully progress on their research journey); responsibilities (the perception that the responsibilities of the postgraduate student and supervisor are clear); research skills (the existence of chances to enhance their essential skills to be capable of overseeing a research venture, analyse the data, and have the capability to learn independently); and professional development (having the opportunities to build their skills in order to manage projects and to develop professional networks).

Therefore, this reported study aims to address this shortcoming by operationalizing the research environment using the multidimensional conceptualization of the postgraduate research experience survey (Neves, 2018). Referencing the Job Demands-Resources model, this study retains the four key aspects of research environment which could be construed as resources from the perspectives of Job Demands-Resources theory: supervision; resources; research community; and professional development.

Doctoral Students' Well-Being and Research Environment

These different aspects of the research environment can be conceptualized as job resources under the Job Demands-Resources model. It also functions as an important antecedent of doctoral students' well-being. For instance, Sverdlik et al. (2018) provided a comprehensive review of the factors (e.g., supervision, financial opportunities, and writing skills) that impact the well-being of doctoral students. Likewise, Jackman and Sisson (2022) found that supervisors were central to navigating the challenges associated with the doctoral journey. Moreover, research suggested that doctoral students' high stress levels could be partly caused or exacerbated by the supervisory relationship (Mackie & Bates, 2019). Additionally, having better institutional resources (Jackman et al., 2022) and university facilities (Ryan et al., 2022) were important predictors of well-being. Furthermore, having a positive research culture (e.g., Jackman & Sisson, 2022) and the conditions to improve one's research skills (McAlpine & Amundsen, 2012) are also key predictors of doctoral students' well-being. Therefore, it was hypothesized that:

H1: The quality of the research environment positively predicts doctoral students' psychological well-being.

Doctoral Students' Well-Being and Consequences

Well-being also has important downstream consequences (Lyubomirsky et al., 2005). Numerous studies have shown that well-being is associated with various adaptive outcomes such as better performance, health, and social relationships (Kansky, 2017). For doctoral students, two important outcomes might be performance (i.e., grades, thesis project, and research productively) and intentions to quit. Past studies have shown that among doctoral students, those with poor mental health were more likely to think about quitting the program (Almasri et al., 2022). Likewise, González-Betancor and Dorta-González (2020) found that students who have suffered anxiety, depression, or discrimination are more likely to interrupt their doctoral studies. Previous studies showed that performance (Daniels & Harris, 2000) and dropout intention (Stubb et al., 2011) can be considered well-being consequences. In consonance with the earlier scholars (Daniels & Harris, 2000; González-Betancor and Dorta-González, 2020; Stubb et al., 2011), the study operationalizes consequences as intentions to quit. Hence, this study examines whether and how well-being would predict doctoral students' intentions to quit. The hypotheses developed are as follows:

H2: Doctoral students' psychological well-being negatively predicts their intentions to quit.

The Role of Well-Being as a mediator in the Effect of Research Environment on Doctoral Students' Intentions to Quit

The different aspects of the research environment are conceptualized as job resources under the Job Demands-Resources model and might serve as important antecedents of doctoral students' well-being. One of the key aspects of research

environment, particularly supervision, can be interpreted as a form of support that doctoral students receive from their faculty. In organizational behaviour research, perceived organizational support is an important antecedent of employee performance, well-being, and turnover (Rhoades & Eisenberger, 2002). The literature on physical well-being, healthy behaviour, and coping has not generally focused on positive affect or positive experience (for some notable exceptions, see Antonovsky, 1988, 1993; Seligman, 1991; Snyder, 2000). Instead, most of the research in this area has examined the effects of hostility, stress, depression, and anxiety (Kubzansky & Kawachi, 2000). The rigorous demands imposed by completing requisite coursework, the comprehensive examination, and the dissertation challenge students' ability to maintain a sense of well-being (Stubb et al., 2011). Studies have found that doctoral students become emotionally exhausted due to heavy workloads and social conflicts (Kurtz-Costes et al., 2006; Maslach, 2003; Rummell, 2015), conflicts within their scholarly community (Stubb et al., 2011), and difficulties with their advisors (Ellis, 2001).

Other research on doctoral students has shown that stress reduces well-being (Moate et al., 2019; Rummell, 2015) and decreases the ability to meet deadlines and complete study-related tasks (Barry et al., 2018). Additionally, dissatisfaction with academia or a particular program of study (Rummell, 2015), faculty members associated with the program (Lovitts, 2002), thesis advisor characteristics (Gill et al., 2012; Godskesen & Kobayashi, 2016; Litalien & Guay, 2015), and aspects of the discipline could all contribute to doctoral student dropout. The conceptual model used in this study identifies the aspects of research environment as predictors of doctoral students'

intentions to quit as consequences and mediated by doctoral students' well-being. Therefore, it was hypothesized that:

H3: Psychological well-being mediates the effects of the quality of research environment on doctoral students' intentions to quit.

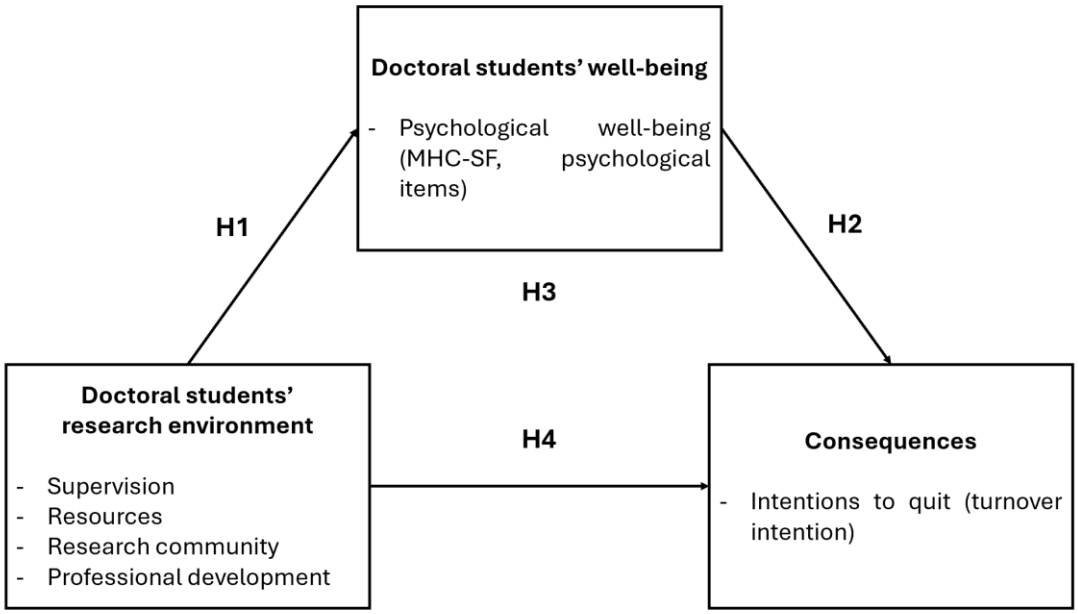
H4: The quality of research environment negatively predicts doctoral students' intentions to quit.

Conceptual Model

This study conceptual model summarizes the theories and the review of literature on the concepts of antecedents, well-being, and consequences discussed in the earlier sections which are quintessential to the research objective (See Figure 1).

Figure 1

Conceptual Model



Chapter Summary

This chapter reviewed key constructs such as research environment, psychological well-being, consequences. In addition, an analysis of peer-reviewed scholarly articles on the effects of antecedents such as aspects of research environment on doctoral students' well-being and the corresponding consequence such as doctoral students' intentions to quit was carried out. A deep dive into literature on Job Demands-Resources model was conducted, specifically on the job demands and job resources and its impact on doctoral students. Relevant literature was reviewed to establish the basis for the choice of the conceptual model, the formulated research questions and hypotheses. The next chapter describes the research methodology, including a description of the population and sampling, and the instrumentation identified for this study. The data collection, data analysis procedures, and ethical issues are also discussed in the next chapter.

Chapter 3: Research Design and Methodology

Introduction

This chapter presents the methodology that was adopted for this study. The objective of this study was to investigate doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources model using quantitative methods. A key aim of this study is to examine the effects of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model as the theoretical basis for this research. A specific goal of this study is to determine the predictive relationship between (1) the research environment as antecedents and (2) the intentions to quit as consequences and doctoral students' well-being using the Job Demands-Resources model.

The chapter begins with a description of the research methodology and research design. A description of the population and sampling, and the instrumentation. The data collection, data analysis procedures, and ethical issues were also outlined in this study. Finally, the chapter concludes with a summary of the methodology used in this study.

Methodology

Rajasekar and Verma (2013) described research methodology as a systematic approach that researchers can adopt to describe, explain, and predict a phenomenon while maintaining the validity, reliability, and integrity of the research being studied (Mathews & Ross, 2010). The aim of this study is to investigate the relationship between doctoral students' well-being and its antecedents and consequences using the Job Demands-Resources (JD-R) perspectives. The research paradigm is largely dependent on the objective of the research which in this case is to examine the effects of research

environment as antecedents of doctoral students' well-being and downstream consequences on doctoral students' intentions to quit; therefore, the choice of quantitative research approach is a justified one.

The approach involves the testing of objective theories by examining the relationship among the variables of doctoral students' well-being, research environment, and intentions to quit (Creswell, 2009). The research is predictive and explanatory in design to achieve the establishment of causal relationship between the antecedents of doctoral students' well-being and the corresponding consequences thereby facilitating the anticipation of phenomena and predict their occurrence (Saunders, Lewis & Thornhill, 2007). An ex post facto design is appropriate for this study as the researcher is trying to establish the linkages between independent and dependent variables, in particular the research environment and doctoral students' well-being (independent variables) on doctoral students' intentions to quit (dependent variable).

Creswell (2017) defined quantitative research as a measure for testing objective theories by investigating the relationship among variables using instruments and data that can be analyzed using statistical procedures. The research design of this study adopts a quantitative approach to investigate doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources model. A correlational research design is formulated to establish the complex relationships between the antecedents of doctoral students' well-being and the corresponding consequences, to predict current events from existing knowledge and information (Curtis et al., 2016; Yukl, 2006). Lunenburg and Irby (2008) emphasized that it is meaningful to use the results of correlational research studies to assess consistency and predict trends. The selection of correlational research

design for this study is an appropriate approach since the objective is to unpack the complex and intertwined relationships between the variables. Therefore, a correlational research design is likely to determine the relationship between the research environment on doctoral students' well-being and its downstream consequences on doctoral students' intentions to quit.

Population and Sampling

The population of interest, as defined by Hossan et al. (2023), refers to a group of individuals or entities that the research is anchored upon including people, pairs, groups, and organizations that can be sampled. Mills and Gay (2016) provided another perspective on the term "population", describing it as a larger group from which the researcher wishes to generalize the findings. The target population refers to a specific group of individuals whom the researcher expresses keen interest in studying. This specific group is constrained by the reach that the researcher has, and it is a representation of the main group of individuals that the researcher is interested in. Ackerman et al. (2019) defined target population as one that has clear qualities or attributes of the group under study, and these outputs apply to a larger 'population of interest.' Referencing the research question, the target population for this study consists of students who are currently pursuing their doctoral degrees. Sampling is defined as the process of identifying individuals, objects, or events from a population that is a representation of a larger group from which they originated (Mills & Gay, 2016). It is an uncommon and impractical feat to simply collect data from the entire population as highlighted by Gay et al. (2012). The primary purpose of survey research is to collect data from a representative sample of the population with the aim to generalize the

findings to the population (Kotrlik et al., 2001). Since each participant was pursuing the same level of qualification, simple random sampling via digital platform, LinkedIn, was selected for this study. Simple random sampling allows every person in a population to have an equal probability of being chosen as a response (Thomas, 2020). The reliance on LinkedIn as the digital platform for recruiting participants introduces self-selection bias. Self-selection bias occurs since the respondents recruit themselves into the survey, rather than being selected (Baker et al., 2010; Kohler, Kreuter, & Stuart, 2019; Mercer et al., 2017). This leads to biased estimates if a variable is correlated with the outcome variable and the response propensity, respectively (Groves, 2006; Mercer et al., 2017). Convenience sampling, a non-probability technique was initially considered but eventually rejected due to the high sampling errors inherent with convenience sampling (Valerio et al., 2016).

It is evident that PLS-SEM performs well with small samples, achieving adequate statistical power requires meeting the minimum sample size thresholds. The appropriate sample size for this research was meticulously calculated using the G*Power software version 3.1.9.7. The analysis was conducted using the option 'Linear multiple regression: Fixed model, R^2 deviation from zero' to accommodate to the multiple predictors in the conceptual framework. This method involved setting several parameters to estimate the necessary sample size effectively. It begins with the selection of the effect size (f^2) of 0.3, aligning to Cohen's (1988) guidelines for a medium effect size, suggesting a balance between sensitivity and resource utilization (Kang, 2021). The significance level (α) was set at 0.05, a standard threshold for statistical significance, while the power (1-β error probability) was targeted at 0.95 to substantially reduce the risk of Type II errors and

ensure 95% confidence in the findings (Wang & Rhemtulla, 2021). The numerator degree of freedom was set to 15, corresponding to the number of predictors presented in the conceptual framework which includes one independent variable with three indicator items and two dependent variables, each with six indicator items. Through these settings, the power analysis calculated that a sample of 106 participants is required to achieve an actual power of approximately 0.9506. The obtained dataset includes 278 responses collected from the sample population. Even after removing responses with missing data, the remaining dataset still exceeds the minimum sample size.

Missing data in survey-based studies can occur as unit non-response (entire surveys) or item non-response (individual unanswered questions). Hair et al. (2022) outline several methods to address the missing data issue in PLS-SEM. These methods include mean replacement which substitutes missing values with the mean of valid responses (suitable for minimal missing data), case wise deletion which removes respondents with missing values, maintaining clean data but potentially reducing the sample size and introducing bias, and pairwise deletion which retains more data using available responses for each computation but results in varying sample sizes, potentially distorting results. Referencing the dataset which consisted of 278 responses exceeding the adequacy threshold, case wise deletion was applied as the most appropriate option to ensure data integrity by removing responses with missing data.

Pilot Study

Boateng et al. (2018) recommended the conduct of a final quality check by administering the survey to a small sample size. Clark and Watson (2016) remind us that while this step may easily be overlooked, it is crucial to refine the scale items further for

ambiguity, missing questions, clarity, and redundancy. Considering the cost-benefit analysis conducted by Johanson and Brooks (2009) to determine the appropriate sample size range, 30 participants were recruited as a pretest to identify any detectable errors. The participants for the pilot study were presented with study information and instructions before proceeding with the questionnaire. The scale scores and demographic data collected during the pilot testing were discarded and not used in the final analysis. The primary objective of this pilot phase is to identify any potential errors, ambiguities, or redundancies in the survey items. The scale was refined and enhanced by addressing these issues before moving on to the primary data collection phase. This phase also served as an opportunity to test the electronic survey and its distribution method which would be utilized for future large-scale data collection endeavours.

Instrumentation

The purpose of instruments in research is to collect data as a test or tool (Gay et al., 2012). An online questionnaire was deployed as an instrument to collect data to address the research question in this study. Gay et al. (2012) explained that an appropriate instrument is pivotal in seeking information that is previously undiscovered by the researchers. Many researchers, such as Cohen et al. (2011), considered questionnaires as one of the most widely used structured instruments for the collection of numerical data. Questionnaires can be deployed to collect information about a particular variable or demographic information about the individual, e.g., age, gender, and work experience. Johnson and Christensen (2024) highlighted the use of questionnaires to gain insights into individuals' attitudes, beliefs, feelings, perceptions, thoughts, behavioural intentions, etc. Therefore, questionnaires are still widely used and remain effective in collecting large

amounts of data in an unambiguous manner (Newby, 2014). Moreover, questionnaires can obtain objective data without compromising confidentiality and anonymity. With confidentiality and anonymity in place, sensitive questions can be asked, and the participants will be encouraged to respond accurately to the questionnaire (Kumar, 2018).

In this research, the instrument deployed for data collection was a structured questionnaire that consisted of demographic information, an adapted version of the respective scales such as Postgraduate Research Experience Survey (PRES) (Bennett & Turner, 2013), Mental Health Continuum-Short Form (MHC-SF) (Keyes, 2009), Intentions to Quit (Mobley, 1977). A well-designed Likert item provides a clear, balanced range of response options that accurately reflect the respondents' attitudes or opinions (Koo & Yang, 2025). For example, a neutral option, such as "Neither Agree nor Disagree", allows respondents to avoid forced choices that might not accurately represent their true perspective. For the 5-item PRES, a five-point rating scale (1 = *Strongly disagree* and 5 = *Strongly agree*) with specific scale labels was assigned to rate the participants' level of agreement to the statements. A total of 6 items was adopted from the MHC-SF to reflect the psychological side of well-being. A six-point rating scale was fixed from 1 (*Never*) to 6 (*Every day*) to represent participants' feeling during the past month to better diagnose individuals' psychological adjustment. Schwarz and Oyserman (2001) considered the frequency rating scale to be more valid than others, as it requires individuals to recall and mentally assess the frequency when one engaged in each behaviour. Three items were chosen and revised from the scale of Mobley (1977) which investigated the intentions to search for another job and intentions to quit. A five-point

rating scale ranging from 1 (*Strongly disagree*) to 5 (*Strongly agree*) was deployed. The complete item wordings are listed in Table 2.

Table 2

Construct and Item Indicators

Construct	Items	
Research Environment	1	My supervisor(s) have the skills to support my research.
	2	I receive timely and constructive feedback from my supervisor(s).
	3	My university provides the necessary research facilities and resources (e.g., labs, software, databases).
	4	I have sufficient access to academic seminars, training, and workshops.
	5	I have opportunities to collaborate with fellow researchers.
	6	I feel that the research environment promotes academic growth.
Psychological Well-being	7	During the past month, how often did you feel happy?
	8	During the past month, how often did you feel that you had something important to contribute to society?
	9	During the past month, how often did you feel satisfied with life?
	10	During the past month, how often did you feel a sense of belonging to a community?
	11	During the past month, how often did you feel that you could handle daily responsibilities well?
	12	During the past month, how often did you feel motivated and optimistic about your research journey?
Intentions to Quit	13	I have considered dropping out of my doctoral program.

14	I frequently think about alternative career or education options.
15	If I were offered a different academic or professional opportunity, I would likely leave this program.

Source: Author's calculations using primary data.

Partial Least Squares Structured Equation Modelling

The use of partial least squares structural equation modelling (PLS-SEM) to analyze complex interrelationships between latent variables and their indicators (Hair et al. 2022; Lohmöller 1989) has recently surged in emerging disciplines such as agriculture, engineering, environmental sciences and ecology, geography, and psychology. The methodological features of PLS-SEM have enabled the researchers' capacities to better understand the complex interrelationships that constitute the "black box" of a variety of attitudinal and behavioural theories, as well as explain and predict unobservable phenomena (Petter 2018; Petter and Hadavi 2021; Russo and Stol 2022). Data characteristics, such as minimum sample size requirements, non-normal data, and scales of measurement (i.e., the use of different scale types), are among the most often stated reasons for applying PLS-SEM across numerous disciplines (e.g., Ghasemy, Teeroovengadum, Becker, & Ringle, 2020; Hair, Sarstedt, Ringle, & Mena, 2012; Ringle et al., 2020). One of the advantages of using PLS-SEM includes the less restrictive assumptions about non-normal data distribution compared to CB-SEM analysis (Ahmad et al., 2021; Hair et al., 2012; Hair et al., 2017; Hair et al., 2019; Richter et al., 2016). Therefore, the use of partial least squares structural equation modelling as a means to analyze complex interrelationships between research environment, doctoral well-being, consequences and their indicators is a valid one. Recent studies published in Journal of Marketing Analytics have used PLS-SEM to assess the effects of COVID-19 related risks

on online shopping behaviour (Soares et al. 2023), the influence of storytelling on the consumer-brand relationship experience (Crespo et al. 2023), and the drivers of consumer trust in live streaming platforms (Leong et al. 2023). Chan and Lay (2018) conducted PLS-SEM statistical analysis with the conclusion that the research instruments (e.g., Science Teaching Efficacy Belief Instrument-Form B, Work Tasks Motivation Scale for Teachers, Dimensions of Attitude towards Science) are reliable and valid in measuring teachers' behavioural intention in teaching science amongst pre-service science teachers in Malaysia.

Validity and Reliability

The two fundamental criteria that determine the quality of instruments and tools in quantitative research are validity and reliability. According to Sürücü and Maslakci (2020), validity refers to how well the instrument measures what it intends to measure. On the other hand, reliability is defined as the consistency of an instrument's results over time and in different situations (Bolarinwa, 2015). Therefore, it is crucial for researchers to ensure that the selected instruments are valid and reliable so that the results are trustworthy and generalizable (Nurfatihah et al., 2021). The reliability of the questionnaire can be determined from the Cronbach's alpha, in particular a value of 0.80 or higher is acceptable for research purposes (Adeniran, 2019; Alfadda & Mahdi, 2021; Yang & Wang, 2019). This boost the researchers' confidence in using the questionnaires where validity and reliability have been established for this study.

Data Collection

The questionnaire was distributed online using Google Forms as part of the study. The sample data was collected using simple random sampling where the populations are

highly homogenous and the members are randomly selected to participate in the research (Bhardwaj, 2019). The questionnaire consisted of three components, first, informed consent was sought from the participants before the start of the survey. Second, the questionnaire began with demographic items consisting of age, gender, doctoral degree type, study year, and discipline area. Lastly, there were a total of 18 items comprising of PRES on a five-point scale (1 = *Strongly disagree* and 5 = *Strongly agree*), MHC-SF (1 = *Never* and 6 = *Every day*), and Mobley (1 = *Strongly disagree* and 5 = *Strongly agree*). Rahi (2017) posited that simple random sampling is often utilized in surveys and quantitative research designs. The questionnaire was administered to a sample of 278 participants comprising of students who were currently pursuing their doctoral degrees. To test the conceptual framework and the formulated hypotheses, Structural Equation Modelling (SEM) was deployed for this study. The SEM was achieved through the "Partial Least Square" (PLS) software version 4 of the Smart-PLS. The PLS-SEM can establish the reliability and validity of the variables which is fundamental to the assessment of any measurement model. Also, the PLS-SEM can also determine the significance of the hypothesized relationships between the variables as shown below.

H1: The quality of the research environment positively predicts doctoral students' psychological well-being.

H2: Doctoral students' psychological well-being negatively predicts their intentions to quit.

H3: Psychological well-being mediates the effects of the quality of research environment on doctoral students' intentions to quit.

H4: The quality of research environment negatively predicts doctoral students' intentions to quit.

Data Analysis Procedures

Statistical analysis of quantitative data was conducted using the "Partial Least Square" (PLS) software version 4 of the Smart-PLS. Prior to feeding the data into PLS for analysis, a detailed examination of the data to identify possible errors was conducted. Hair et al. (2014) advocated that several types of quality checks should be made prior to analysing the structural model when using PLS-SEM. The first of these checks is to look for missing data (Hair et al., 2014). If missing data are found, they can be replaced by the estimated value of the associated indicator, or by the case that has missing values (Hair et al., 2014; Mertler & Vannatta, 2010). In addition to checking for missing data, suspicious response patterns, such as response-set, were also examined (Hair et al., 2014; Levy, 2008). Inconsistent answers should also be screened (Hair et al., 2014). Next, outliers, or cases with unusual or extreme values, would be identified using Mahalanobis distance (Mertler & Vannatta, 2010). If outliers exist, a decision was made whether to drop the cases or to acknowledge the existence of a subgroup (Hair et al., 2014; Mertler & Vannatta, 2010). The final screening was to check the skewness and kurtosis of the data (Hair et al., 2014).

Next, the researcher performed the analysis to derive descriptive statistics - mean, standard deviation, and range - to get an overview of the data. Subsequently, Structural Equation Modelling (SEM) was operated through PLS software for the establishment of causal relationship between the antecedents of doctoral students' well-being and the corresponding consequences on doctoral students' intentions to quit. Performing SEM

through PLS can establish the validity and reliability of the tenets which is fundamental to the assessment of any measurement models. Path analysis was conducted to measure the effects of the tenets as articulated in the hypotheses. Finally, these findings based on the collected data were analysed and reported as part of the research.

While this study provides invaluable insights into the antecedents and consequences affecting doctoral students' well-being, it is essential to acknowledge the study's inherent limitations. Limitations are an essential aspect of any research study that the researchers need to recognize for their potential negative impact on the research outcomes (Gay et al., 2012). The research design for this study is quantitative in nature, depending solely on survey for data collection which is susceptible to potential response bias. The choice of employing probability sampling method (Valerio et al., 2016), particularly simple random sampling, is an unbiased and impartial selection method. Stockemer (2019) asserts that randomization helps to offset the confounding effects of known and unknown factors by choosing participants which may lead to a more considerate sample selection process for the study.

Ethical Issues

In this study of the antecedents and consequences affecting doctoral students' well-being, establishing and maintaining trust and confidentiality is of utmost important. As part of the requirements for a doctorate study, an application for ethical clearance was submitted and subsequently approved by the European International University. The requirements included completion of the literature review, research proposal and data collection instrument. The access to the research data was limited only to the researcher, and strict disposal procedures of manual and digital data were in place. Ethical clearance

was obtained to emphasize that the study was anonymous, and collection of personal data was not required. Prior to the commencement of the survey, it was highlighted that the participants could choose not to participate and could also stop participating at any time without any negative consequences.

Noteworthy, the Google Cloud's robust security and privacy controls are aligned with the requirements of the Personal Data Protection Act (PDPA) (Roy et al., 2021). The study sampling and data collection informs the participant that it collects minimum personally identifiable information (PII). Furthermore, Google Forms does not collect survey participants' IP addresses, nor does it place cookies on the respondents' computer devices. These measures are in place to protect the participants from potential harm and ensure confidentiality throughout the research process. The consent at the beginning of the survey also informs the participants that collected data are analysed in aggregate and does not target the participant's gender, age, or other demographic data.

The study's collected data is stored in encrypted storage with restricted access. As mentioned earlier, only authorized personnel who are required to complete and review the research process have access to the data. These data protection mechanisms alleviate any data confidentiality and security concerns.

Chapter Summary

This chapter furnished an encyclopaedic narration of the methodology employed for this quantitative research. A correlational research design was employed to establish the prevalence of relationships between the research environment on doctoral students' well-being and its downstream consequences on doctoral students' intentions to quit. For this study, Google Forms was used as an online survey platform for the distribution of the

survey to the 278 participants through simple random sampling. The collected data provided necessary insights to examine the effects of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model. Finally, adherence to the ethical standards and the rights of the participants are protected.

Chapter 4: Presentation of Results

Introduction

The objective of this study was to investigate doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources model using quantitative method. A key aim of this study is to examine the effects of the quality of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model as the theoretical basis for this research. A specific goal of this study is to determine the predictive relationship between (1) the research environment as antecedents and (2) the intentions to quit as consequences and doctoral students' well-being using the Job Demands-Resources model. The questionnaire was distributed online using Google Forms as part of the study.

This chapter begins with a recap of the research questions and hypotheses formulated for this study. Descriptive statistics and analysis of measurement model were also presented in great length. Next, the proposed conceptual framework was examined to establish the strength of the hypothesized relationships in this study. Finally, the chapter concluded with a summary of the analysis of the data for this study.

Research Questions & Hypotheses

To address the objective of investigating the research environment as antecedents of doctoral students' well-being and their downstream impact on doctoral students' intentions to quit. The research will attempt to address the following questions and associated hypotheses:

1. To investigate the impact of research environment as antecedents on doctoral students' well-being.

H1: The quality of the research environment positively predicts doctoral students' psychological well-being.

2. To examine the downstream impact of doctoral students' well-being on their intentions to quit.

H2: Doctoral students' psychological well-being negatively predicts their intentions to quit.

3. To analyze the mediating role of doctoral students' well-being between the research environment and doctoral students' intentions to quit.

H3: Psychological well-being mediates the effects of the quality of research environment on doctoral students' intentions to quit.

H4: The quality of research environment negatively predicts doctoral students' intentions to quit.

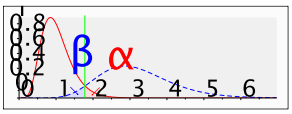
Description of the Sample

This study utilized simple random sampling, where the populations are highly homogenous and the members are randomly selected to participate in the research. The sample was collected from LinkedIn universities' interest groups across the Asia region. The only inclusion criterion for this study is that the participants are current doctoral students pursuing their studies across the Asian region. An a-priori analysis through G*Power software version 3.1.9.7 initially calculated that a minimum sample of 106 responses were required for a power of 0.80, with significance level (α) set at 0.05, and the effect size (f^2) of 0.3. The post-hoc G*Power analysis calculated that the power of the

actual sample is 0.9506. Even after removing responses with missing data, the remaining dataset at 278 far exceeds the minimum sample size of 106 and has a stronger power. The result of this analysis is provided in Figure 2.

Figure 2

*Post-Hoc G*Power Analysis*



Quantitative Data Analysis

The quantitative data analysis employed Structural Equation Modelling (SEM) to investigate the relationships between the effects of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model using "Partial Least Square" (PLS) software version 4 of the Smart-PLS.

Descriptive Statistics of Demographic Information

Descriptive statistics collected via the questionnaire included factors such as gender, age, doctoral degree type, study year, and discipline area. Table 3 displays a comprehensive overview of the demographic characteristics of 278 participants who took part in this study. Insights into the study's diversity and representation can be gleaned from the sample's demographic snapshot. There is a total of 278 valid respondents. From

the data collected, 32% of the respondents were male, 25.9% were female, 21.2% were non-binary/third gender, and lastly, 20.9% preferred not to say. Amongst the respondents, approximately 56.5% reported pursuing a PhD degree while the remaining 43.5% were pursuing professional doctorate degree such as DBA, EdD. Based on the dataset, the years of study amongst the respondents were well spread with 16.2% for year 1, 20.1% for year 2, 28.1% for year 3, 17.6% for year 4, and 18.0% for year 5 or above. Majority of the respondents (37.8%) were in the discipline area of business/professions, with the second majority (33.8%) in the discipline area of humanities, while the remaining 28.4% in the discipline area of science/engineering. Lastly, the average age of the respondents was 37.3 years with a standard deviation of 1.263.

Table 3

Demographic Information of Survey Participants (N = 278)

Item	Responses	(%)
1. Gender		
Male	89	32.0%
Female	72	25.9%
Non-binary / third gender	59	21.2%
Prefer not to say	58	20.9%
2. Age		
<25	36	12.9%
26 - 35	57	20.5%
36 - 45	78	28.1%
46 - 55	62	22.3%
>55	45	16.2%
3. Doctoral Degree Type		
PhD degree	121	43.5%
Professional Doctorate (e.g., DBA, EdD)	157	56.5%
4. Study Year		
Year 1	45	16.2%
Year 2	56	20.1%
Year 3	78	28.1%

Year 4	49	17.6%
Year 5 or above	50	18.0%
5. Discipline Area		
Humanities	94	33.8%
Science/Engineering	79	28.4%
Business/Professions	105	37.8%

Source: Author's calculations using primary data.

Descriptive Statistics of Latent Variables

The next section of this paper reports on the descriptive statistics of each latent variable in the conceptual model of this study: Research Environment (PRES), Mental Health Continuum Short Form (MHC-SF), and Intentions to Quit (MS). The following descriptive statistics are included for each latent variable, minimum, maximum, mean, standard deviation, kurtosis, and skewness.

Research Environment

A detailed summary of the descriptive statistics derived from Partial Least Squares (PLS) for six items (PRES1 to PRES6) was reported for a total of 278 participants. For the range of all the items, there is a minimum score of 1 and maximum score of 5 on a 5-point Likert scale. The mean values illustrate the central tendency of the data ranging from 3.050 (PRES5) to 3.209 (PRES2), implying a trend towards the mid-range of the 5-point scale. The dispersion of the data is represented by the standard deviation values ranging from 1.34 to 1.416. The dispersion of data in a normal distribution is represented by the standard deviation value. A large standard deviation value suggests that the data points are widely distributed from the average, indicating a high presence of variability in the data. On the other hand, a small standard deviation value suggests that the data points were closely clustered around the average, indicating low variability in the data. The data from the sample size of 278 met the assumptions of normality (-1.311 to -1.084) for

kurtosis and (-0.270 to -0.051) for skewness that is essential for structured equation modelling (Kline, 2011). Kurtosis measures the 'peakedness' of a distribution while skewness measures the symmetry of the variable distribution. The kurtosis values for all items were negative and below 3 ranging from -1.311 (PRES5), -1.255 (PRES3), -1.207 (PRES6), -1.178 (PRES4), -1.139 (PRES1) and -1.084 (PRES2), displaying a platykurtic distribution. The skewness values were relatively low for all items ranging from -0.270 (PRES2), -0.213 (PRES4), -0.209 (PRES1), -0.142 (PRES6), -0.122 (PRES3), and -0.051 (PRES5), displaying a left skewed distribution which is less prone to producing outliers (Cain et al., 2017; Westfall & Henning, 2013). Both the kurtosis and skewness of the data were between the recommended value of -2.58 and 2.58, justifying the normality assumptions to qualify the data for further analysis through structured equation modelling (Sovey et al., 2022). In addition, the summary of descriptive statistics is essential in ensuring that the analysis distilled from the study is established on vigorous and elaborate empirical evidence. Table 4 reports on the descriptive statistics of Research Environment indicator items.

Table 4

Descriptive Statistics of Research Environment Indicator Items

	Min	Max	Mean	Std Dev	Kurtosis	Skewness
PRES1	1	5	3.119	1.34	-1.139	-0.209
PRES2	1	5	3.209	1.346	-1.084	-0.270
PRES3	1	5	3.054	1.384	-1.255	-0.122
PRES4	1	5	3.140	1.354	-1.178	-0.213
PRES5	1	5	3.050	1.416	-1.311	-0.051
PRES6	1	5	3.068	1.354	-1.207	-0.142

Source: Author's calculations using primary data.

Doctoral Students' Well-Being

A detailed summary of the descriptive statistics derived from PLS for six items (MHC-SF1 to MHC-SF6) was reported for a total of 278 participants. For the range of all the items, there was a minimum score of 1 and a maximum score of 6 on a 6-point Likert scale. The mean values illustrate the central tendency of the data ranging from 3.719 (MHC-SF5) to 3.504 (MHC-SF1), implying a trend towards the mid-range of the 6-point scale. The dispersion of data is represented by the standard deviation values ranging from 1.615 to 1.771. The dispersion of data in a normal distribution is represented by the standard deviation value where the magnitude of the value determines the presence of variability in the data. After evaluation by using skewness and kurtosis, the normality of the data was not affected (Tabachnick & Fidell, 2013). Correspondingly, the kurtosis and skewness were normally distributed since the values were within the adequate ranges for normality (-1.357 to -1.131) for kurtosis and (-0.186 to -0.063) for skewness respectively which is below the value of 3.0 and 10.0 (Kline, 2023). Kurtosis measures the 'peakedness' of a distribution while skewness measures the symmetry of the variable distribution. The kurtosis values for all items were negative and below the value of 3.0 ranging from -1.357 (MHC-SF5), -1.263 (MHC-SF4), -1.224 (MHC-SF3), -1.186 (MHC-SF1), -1.184 (MHC-SF2), and -1.132 (MHC-SF6), displaying a platykurtic distribution. The skewness values were relatively low for all items ranging from -0.186 (MHC-SF5), -0.130 (MHC-SF2), -0.125 (MHC-SF6), -0.082 (MHC-SF4), -0.076 (MHC-SF3), and -0.063 (MHC-SF1), displaying a left skewed distribution which is less prone to producing outliers (Cain et al., 2017; Westfall & Henning, 2013). The inclusion of descriptive statistics is fundamental in ensuring that the analytical interpretations derived from this

study are substantiated by rigorous and comprehensive empirical evidence. Table 5 reports on the descriptive statistics of Doctoral Students' Well-Being indicator items.

Table 5

Descriptive Statistics of Doctoral Students' Well-Being Indicator Items

	Min	Max	Mean	Std Dev	Kurtosis	Skewness
MHC-SF1	1	6	3.504	1.615	-1.186	-0.063
MHC-SF2	1	6	3.637	1.665	-1.184	-0.130
MHC-SF3	1	6	3.558	1.643	-1.224	-0.076
MHC-SF4	1	6	3.55	1.718	-1.263	-0.082
MHC-SF5	1	6	3.719	1.771	-1.357	-0.186
MHC-SF6	1	6	3.612	1.643	-1.131	-0.125

Source: Author's calculations using primary data.

Consequences as Intention to Quit

A comprehensive summary of the descriptive statistics generated through PLS for the six measurement items (MS1 to MS6), based on the data collected from a sample of 278 participants. Across all six measurement items, scores range from minimum score of 1 to a maximum score of 5, consistent with the 5-point Likert scale employed for this study. The mean scores, ranging from 2.824 (MS3) to 3.288 (MS6), reflect the central tendency of the dataset and suggest a general inclination towards mid-range of the 5-point Likert scale. The dispersion of the data was represented by the standard deviation values, ranging from 1.331 to 1.396. The dispersion of data in a normal distribution is represented by the standard deviation value. A large standard deviation value suggests that the data points were widely distributed from the average, indicating a high presence of variability in the data. On the other hand, a small standard deviation value suggests that the data points were closely clustered around the average, indicating low variability in the data. According to Tabachnick and Fidell (2013), deviations in skewness and kurtosis are unlikely to significantly impact the assumption of normality when the sample

size exceeds 200 participants. The kurtosis and skewness ranged from -1.273 to -1.044 and -0.387 to 0.019 respectively which was below the value of 3.0 and 10.0 (Kline, 2023). Kurtosis measures the 'peakedness' of a distribution while skewness measures the symmetry of the variable distribution. The kurtosis values for all items were negative and below 3 ranging from -1.273 (MS5), -1.266 (MS1), -1.265 (MS4), -1.257 (MS3), -1.086 (MS2), and -1.044 (MS6), displaying a platykurtic distribution. The skewness values were relatively low for all items ranging from -0.387 (MS6), -0.264 (MS2), -0.100 (MS4), -0.093 (MS1), 0.005 (MS5), and 0.019 (MS3), displaying a left skewed distribution which is less prone to producing outliers (Cain et al., 2017; Westfall & Henning, 2013). The observed values for kurtosis and skewness fell within the acceptable range of -2.58 to 2.58, thereby supporting the assumption of normality required for subsequent analysis using structural equation modelling (Sovey et al., 2022). Table 6 reports the descriptive statistics of Intentions to Quit indicator items.

Table 6

Descriptive Statistics of Intention to Quit Indicator Items

	Min	Max	Mean	Std Dev	Kurtosis	Skewness
MS1	1	5	3.047	1.368	-1.266	-0.093
MS2	1	5	3.187	1.331	-1.086	-0.264
MS3	1	5	2.824	1.358	-1.257	0.019
MS4	1	5	2.993	1.391	-1.265	-0.100
MS5	1	5	2.993	1.396	-1.273	0.005
MS6	1	5	3.288	1.369	-1.044	-0.387

Source: Author's calculations using primary data.

Measurement Model Analysis

The PLS-SEM is a causal modelling approach that focuses on prediction in estimating statistical models, and the structure is designed to present possible causal explanations (Wold, 1982; Sarstedt et al., 2017). For data analysis, PLS-SEM techniques

were employed using Smart-PLS version 4 to assess measurements and structural models. In consonance with Hair et al. (2019), the following four assessments of measurement models in PLS-SEM included the factors' loading, convergent validity, reliability of internal consistency, and discriminant validity.

Factor Loadings

Factor loading is defined as "the extent to which each of the items in the correlation matrix correlates with the given principal component. Factor loadings can range from -1.0 to 1.0, with higher absolute values indicating a higher correlation of the items with the underlying factor" (Pett, Lackey & Sullivan, 2003, p. 299). All the items except for PRES6, MHC-SF3, MHC-SF4, MS1, MS3, MS4 and MS5 had a factor loading lower than the recommended value of 0.50 (Sarstedt et al., 2021). Henceforth, the aforementioned factors were removed from the model. The complete list of factor loadings is presented in Table 7.

Table 7

Factor Loading

	MHC-SF	MS	PRES
MHC-SF1	0.711		
MHC-SF2	0.744		
MHC-SF5	0.820		
MHC-SF6	0.908		
MS2		0.897	
MS6		0.911	
PRES1			0.721
PRES2			0.762
PRES3			0.773
PRES4			0.832
PRES5			0.592

Source: Author's calculations using primary data.

Indicator Multicollinearity

Fornell and Bookstein (1982) defined Variance Inflation Factor (VIF) statistics as the assessment of any potential multicollinearity amongst the indicators. Sarstedt et al. (2021) explained that multicollinearity is not detrimental to a study if the VIF value is lower than 5.0. All the indicators presented VIF values that range between 1.188 to 4.311 which is lower than the recommended threshold of 5.0. The completed list of multicollinearity statistics for indicators is presented in Table 8.

Table 8

Multicollinearity Statistics (VIF) for Indicators

	VIF
MHC-SF1	1.595
MHC-SF2	2.194
MHC-SF5	1.937
MHC-SF6	2.531
MS2	1.679
MS6	1.679
PRES1	3.975
PRES2	4.311
PRES3	2.685
PRES4	2.928
PRES5	1.188

Source: Author's calculations using primary data.

Convergent Validity

"Convergent validity is the degree to which multiple attempts to measure the same concept are in agreement. The idea is that two or more measures of the same thing should covary highly if they are valid measures of the concept" (Bagozzi, Yi & Phillips, 1991, p. 425). In this study, Average Variance Extracted (AVE) was used to assess and justify convergent validity. Fornell & Larcker (1981) asserted that the AVE value must be greater than or equal to the recommended value of 0.50 before convergent validity can be established. The AVE values for all the constructs ranged between 0.548 to 0.818

which is greater than the recommended value of 0.50, justifying the assertion of convergent validity in this study. Table 9 presents the complete list of AVE values.

Table 9

Construct Convergent Validity

	Average variance extracted (AVE)
MHC-SF	0.639
MS	0.818
PRES	0.548

Source: Author's calculations using primary data.

Internal Consistency Reliability

Mark (1996) stated that, "Reliability is defined as the extent to which a measuring instrument is stable and consistent. The essence of reliability is repeatability. If an instrument is administered repeatedly, will it yield the same results" (p. 285). In this study, Cronbach Alpha (CA), and Composite Reliability (CR) were used for measuring reliability. The values for CA and CR should be from 0 to 1. The Cronbach Alpha values ranged between 0.778 to 0.812, whereas Composite Reliability statistics ranged between 0.857 to 0.900. The results for construct reliability analysis are presented in Table 10. Cronbach Alpha and Composite Reliability as indicators of reliability exceeded the required threshold of 0.70, ranging for Cronbach Alpha between 0.778 to 0.812 and between 0.857 to 0.900 for Composite Reliability (Hair, Ringle & Sarstedt, 2011). Henceforth, construct reliability was established in this study.

Table 10

Construct Reliability Analysis (Cronbach Alpha and Composite Reliability)

	Cronbach's alpha	Composite reliability
MHC-SF	0.812	0.875
MS	0.778	0.900
PRES	0.792	0.857

Source: Author's calculations using primary data.

Discriminant Validity

"Discriminant validity is the degree to which the measures of different concepts are distinct. The notion is that if two or more concepts are unique, then valid measures of each should not correlate too highly" (Bagozzi et al., 1991, p. 425). The discriminant validity was determined by a combination of Fornell & Larcker criteria, cross loadings, and HTMT ratio.

Fornell & Larcker Criterion. In this study, discriminant validity was established as the square root of AVE (in Bold and Italics) for all the constructs that were greater than their correlation with other constructs (Fornell & Larcker, 1981). For example, the value of MHC-SF factor (0.799) was greater than all its shared variances: the MS factor (0.632), and the PRES factor (0.412), justifying the establishment of discriminant validity in this study. The complete list of Fornell and Larcker criteria was presented in Table 11.

Table 11

Discriminant Validity – Fornell & Larcker Criterion

	MHC-SF	MS	PRES
MHC-SF	***0.799***		
MS	0.632	***0.897***	
PRES	0.412	0.631	***0.740***

Source: Author's calculations using primary data.

Cross Loadings. Cross loadings refer to the assessment of the loading strength of an item on the underlying construct amongst all the remaining constructs of interest. The factor loading of all the items should be greater than the underlying construct as compared to the other constructs in the study (Wasko & Faraj, 2005). In the present study, the outer loadings for every construct were greater than the other constructs' loadings. For example, the indicators within the construct of MHC-SF (MHC-SF1, MHC-SF2, MHC-SF5, MHC-SF6) had the highest loadings of 0.711, 0.744, 0.820, and 0.908

when compared to other constructs' loadings, e.g., MS2 = 0.468, MS6 = 0.669, PRES1 = 0.283, PRES2 = 0.123, PRES3 = 0.269, PRES4 = 0.419, and PRES5 = 0.319. Henceforth, it was concluded that discriminant validity is established in this study. Table 12 presents cross loadings for all the constructs.

Table 12

Discriminant Validity – Cross Loadings

	MHC-SF	MS	PRES
MHC-SF1	0.711	0.481	0.224
MHC-SF2	0.744	0.229	0.330
MHC-SF5	0.820	0.488	0.227
MHC-SF6	0.908	0.681	0.479
MS2	0.468	0.897	0.634
MS6	0.669	0.911	0.513
PRES1	0.283	0.478	0.721
PRES2	0.123	0.306	0.762
PRES3	0.269	0.436	0.773
PRES4	0.419	0.508	0.832
PRES5	0.319	0.510	0.592

Source: Author's calculations using primary data.

Heterotrait-Monotrait (HTMT) Ratio. HTMT ratio was established via the calculation of differences of the association between the constructs. This ratio plays a pivotal role in establishing discriminant validity. However, the threshold for HTMT ratio has yet to reach a consensus among scholars. Kline (2011) proposed a threshold of 0.85 or less, while Teo, Srivastava and Jiang, (2008) recommended a liberal threshold of 0.90 or less. The average correlation between all indicators is deemed satisfactory as the HTMT values were lower than required threshold at 0.734, 0.464, and 0.774 respectively. Table 13 shows that the HTMT values for this study were lower than the required threshold of 0.90. Therefore, discriminant validity evaluation fully supports the discriminant validity for this study.

Table 13

Discriminant Validity – HTMT

	MHC-SF	MS	PRES
MHC-SF			
MS	0.734		
PRES	0464	0.774	

Source: Author's calculations using primary data.

Heterotrait-Monotrait (HTMT) Confidence Intervals. HTMT confidence intervals were established through bias-corrected and accelerated confidence intervals. In this study, the discriminant validity was assessed through the values of confidence intervals shown in Table 14. The range of the confidence interval should be in range below 1. If a value of "1" is displayed in upper bound, this indicates that the item used has poor discriminant validity (Henseler et al., 2015). Since none of the confidence intervals range exceed the value of "1", the constructs are empirically distinct, confirming discriminant validity based on HTMT criterion with bootstrapping.

Table 14

Discriminant Validity – Confidence Intervals

Hypothesized relationships	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
PRES → MHC-SF	0.448	0.435	0.258	0.607
MHC → MS	0.412	0.441	0.239	0.547
PRES → MHC-SF → MS	0.185	0.192	0.091	0.306
PRES → MS	0.447	0.452	0.262	0.587

Source: Author's calculations using primary data.

Structural Model Analysis

The next course of action in data analysis was to examine the significance and strength of the hypothesized relationships in the proposed model for this study. Investigating the model's predictive powers was an essential component of the structural model's calculation, including the examination of path coefficients, indirect effects, total

effects, outer loadings, as well as other invaluable insights. According to Hair et al. (2019), the PLS-SEM technique can overcome the distinct dichotomy between explanations emphasized in academic research and prediction which establishes the basis for managerial implications. Path analysis was employed to examine the direct and indirect linear relationship between the constructs in this study. Lei and Wu (2007) elaborated that path analysis is one of the best approaches for studying the relationship between constructs, as well as uncovering the causality between constructs since the causal relationships present a profound and authentic understanding.

SEM is often referred to as causal modelling (Wuensch, 2009). Almahamid and Rub (2011) described the use of linear regression analysis to establish the allotment of a construct's variance in the model, and it was represented by standardized regression coefficients, R^2. Furthermore, standardized regression coefficients, R^2, are often employed to determine the relative significance of predictor variables (Anglim, 2007), while path coefficients indicate the strength of the relationship between the variables (Chin, 1998). Figure 3, 4 and Table 15 report the path coefficient and loading value of each path lines within the PLS algorithm procedure. The highest t-value was derived from the path between PRES → MS (t = 5.609), while the lowest value came from the indirect relationship between PRES → MHC-SF → MS (t = 3.242). All the three hypotheses proposed in this study were supported. The relationship between PRES → MHC-SF (β = 0.412, t = 5.115, $p < 0.05$), with a 95% confidence interval of [0.258, 0.607], H1, was supported. Similarly, the relationship between MHC-SF → MS (β = 0.448, t = 4.096, $p < 0.05$), with a 95% confidence interval of [0.239, 0.547], H2, was

supported. Lastly, PRES → MS ($\beta = 0.447$, t = 5.609, $p = p < 0.05$), with a 95% confidence interval of [0.262, 0.587], H4, was supported.

The bootstrapping indirect effects are more robust in reporting mediation analysis (Hayes, 2017; Ramayah et al., 2018). Hayes (2017) urged that the bias-corrected bootstrap confidence interval is the most ideal approach for detecting mediating effects in scientific research. The indirect results obtained through the bootstrapping analysis with 5000 re-samples demonstrated that H3 ($\beta = 0.185$, t = 3.242, $p < 0.05$), with a 95% confidence interval of [0.091, 0.306], was significant.

Table 15

Structural Path Analysis Result

Number Hypothesis	Hypothesized relationships	Path	t-Values	*p*-Values	Results
H1	PRES → MHC-SF	0.412	5.115	0.000	Accepted
H2	MHC → MS	0.448	4.096	0.000	Accepted
H3	PRES → MHC-SF → MS	0.185	3.242	0.001	Accepted
H4	PRES → MS	0.447	5.609	0.000	Accepted

Source: Author's calculations using primary data.

Figure 3

Path Coefficient Results and p-Values for the Conceptual Model

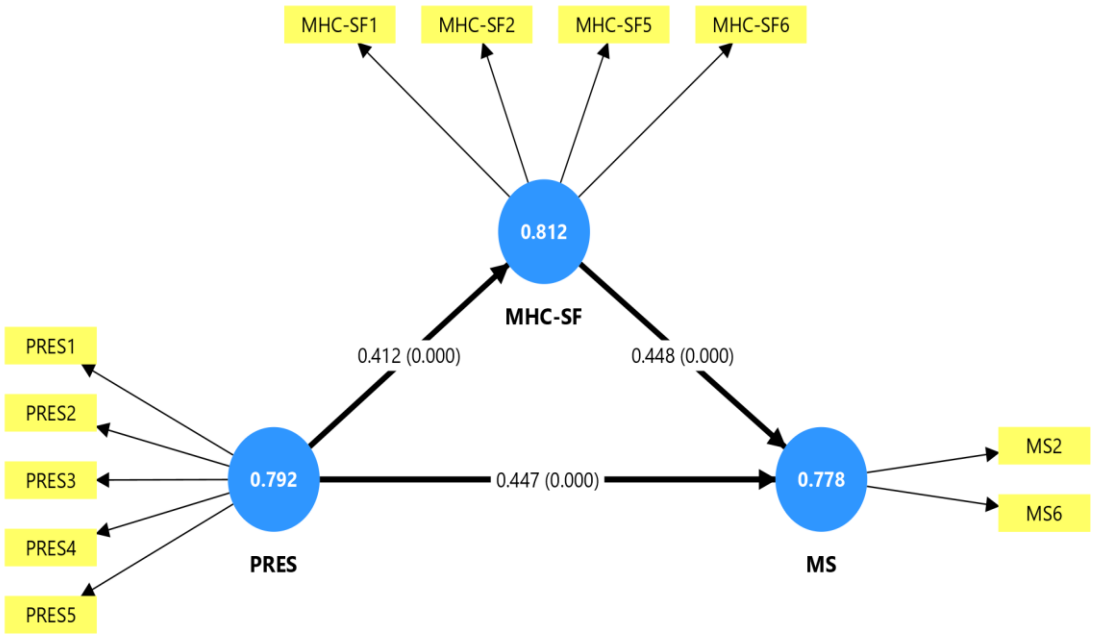
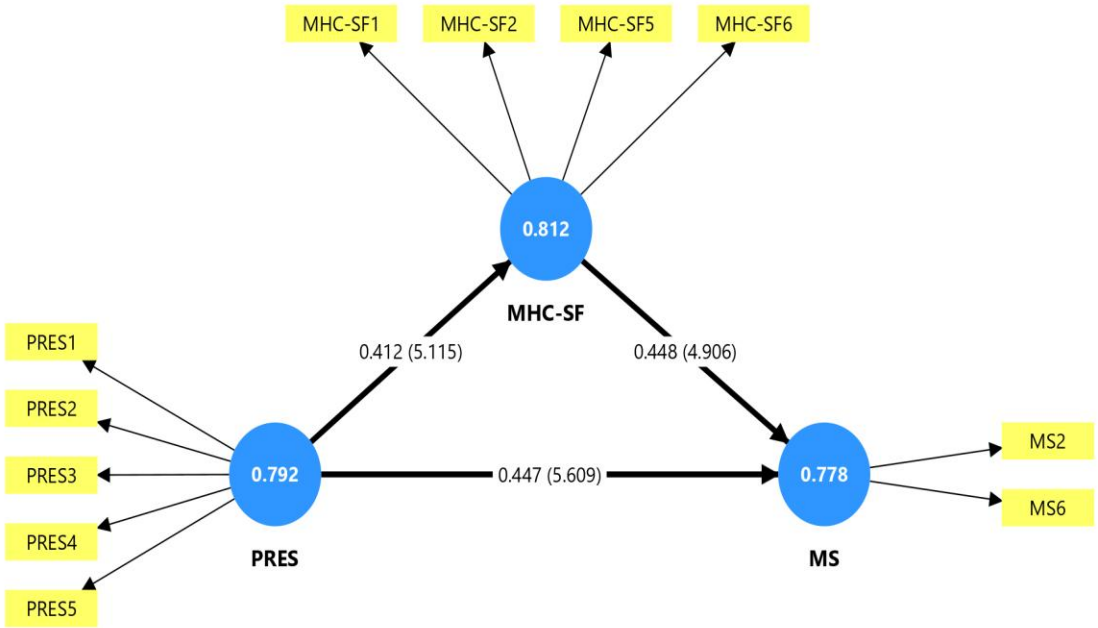


Figure 4

Path Coefficient Results and t-Values for the Conceptual Model



Explanatory Power Results

In evaluating the model performance metrics reported for the study's conceptual model, the R-square and the R-square adjusted values provide insights into the model's explanatory power. R-square (R^2) is a statistical measure representing the proportion of the variance for a dependent variable explained by an independent variable or variables in a regression model. For MS, the R^2 value is 0.565 which suggests that approximately 56.5% of the variance in the dependent variable can be explained by the independent variables included in the model. A higher R^2 value indicates a model that explains a significant amount of variance which can be interpreted as having a strong effect size.

R^2 adjusted, also known as the adjusted R^2, modifies the R^2 value to account for the number of predictors in the model. This adjustment helps to penalize the addition of non-contributory predictors to the model, providing a more accurate and conservative estimate of the model's explanatory power. For MS, the R^2 adjusted value is 0.556. The fact that this value is slightly lower than the R^2 (0.565) but still relatively close indicates that the model does not contain many unnecessary predictors, and the included predictors contribute significantly to explaining the variance in the dependent variable (Purwanto, 2021).

Overall, these values indicate that the conceptual model is robust, with both moderate R^2 and R^2 adjusted values suggesting moderate explanatory power and effective control over potential overfitting through adjusting the number of predictors. This effective balance between complexity and explanatory power enhances the model's utility in practical applications or further research within the study's framework (Lin et al., 2020). The proximity of the R^2 to the R^2 adjusted also implies a well-specified model that

is appropriately fitted to the data without redundancy (Hair et al., 2021). Table 16 below shows the R-square and R-square adjusted.

Table 16

R-square and R-square adjusted

	R^2	R^2 adjusted
MS	0.565	0.556

Source: Author's calculations using primary data.

Effect Size Results

Evaluating the impact of predictor variables on a dependent variable, Intentions to Quit (MS), is crucial for understanding their relative importance and influence within the model. This analysis involves assessing path coefficients, effect sizes, and statistical significance to effectively delineate the relationships among constructs.

The assessment of the explanatory power is performed using the coefficient of determination (R^2) and the effect size (f^2). R^2 ranges from 0 to 1. The values for f^2 are 0.02 (small), 0.15 (medium), and 0.35 (large). As indicated by f-square (f^2), the effect size reveals substantial differences in how various predictors impact MS. Notably, research environment (PRES) and psychological well-being (MHC-SF) exhibit a profound influence with an f^2 of 0.381 and 0.383 respectively, considered as a large effect size (Cohen, 1988). The f^2 value suggests that the research environment and psychological well-being of doctoral students are key in influencing their intentions to quit.

Statistical significance further supports these insights. The significant influence of both research environment and doctoral students' psychological well-being on doctoral students' intention to quit are statistically confirmed with a *t*-statistic of 5.609 and 4.096, and a *p*-value of 0.000 and 0.000, reinforcing its impact as predictor variables. In

summary, the R^2 and effect size analysis underscores the importance of research environment and doctoral students' psychological well-being on their intentions to quit. Table 17 below shows the overall effect size of exogenous variables on the endogenous variable.

Table 17

Overall Effect Size of Exogenous Variables on the Endogenous Variable

Hypothesized relationships	f^2	T-Values	p-Values
MHC → MS	0.383	4.096	0.000
PRES → MS	0.381	5.609	0.000

Source: Author's calculations using primary data.

Predictive Relevance Results

The PLS-predict technique is quintessential to assessing a model's predictive relevance and accuracy (Shmueli, 2016). This technique employs key metrics such as Q^2 (Predictive Squared Correlation Coefficient), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) to evaluate how effectively a model can predict new, unseen data. These indicators are essential for confirming the external validity of SEM models, such as those developed to understand the predictors of doctoral students' intentions to quit (Shmueli et al., 2019).

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The Q^2 value for MS construct in the conceptual model is 0.385. This substantial value, significantly greater than 0, indicates that the model possesses considerable predictive relevance. A Q^2 value above 0 suggests that the model can effectively predict unseen data which is crucial for practical application within the psychology field. The value of 0.385 implies that the model can effectively predict approximately 38.5% of the variance in MS, demonstrating its moderate predictive power (Shmueli et al., 2019)

Additionally, the RMSE and MAE values provide further insights into the model's predictive accuracy. The RMSE value for MS is reported at 0.529, indicating that, averagely, the model's prediction deviate from the actual observed values by 0.529 units. In predictive modelling, lower values of RMSE are preferable as it indicate more accurate predictions. Similarly, the MAE value for MS is reported at 0.396, suggesting that the model predicts doctoral students' intentions to quit with an average deviation of approximately 0.396 units from the actual scores. Lower MAE values also indicate better predictive accuracy, reinforcing the model's utility in practical scenarios (Sharma et al., 2023; Shmueli et al., 2019).

The predictive analysis results from the PLS-predict technique for the conceptual model suggest strong predictive capabilities. The high Q^2 value confirms the model's efficacy in terms of external validity and its practical utility in forecasting outcomes based on the model's constructs (Shmueli et al., 2019). Meanwhile, the RMSE and MAE values offer insights into the model's precision in prediction, suggesting it performs commendably in predicting doctoral students' intention to quit within the field of psychology. These metrics collectively highlight the model's robustness and reliability, affirming its role as a valuable tool in understanding the predictors of doctoral students'

intention to quit (Sharma et al., 2023). Table 18 below shows the PLS-predict results of conceptual model.

Table 18

PLS-predict Results of Conceptual Model

	Q^2	RMSE	MAE
MS	0.385	0.529	0.396

Source: Author's calculations using primary data.

Model Quality

To assess the quality of the structural model, this study evaluated several key indicators of predictive accuracy and explanatory power. Specifically, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) were examined, as presented in the preceding sections. These measures are widely recognized in the PLS-SEM literature as essential for determining the explanatory strength of latent constructs and the predictive capability of the model (Chin, 1998; Hair et al., 2017; Henseler et al., 2009). In addition to these measures, the Standardized Root Mean Square Residual (SRMR) was assessed for both the saturated and estimated models.

The reported SRMR value of 0.051 indicates a satisfactory fit, as values below 0.08 are generally considered acceptable and reflective of good model adequacy (Benitez et al., 2020; Hair et al., 2021; Hu & Bentler, 1998, 1999). The SRMR has increasingly been adopted as a diagnostic tool in PLS-SEM, providing an approximate measure of the discrepancy between observed and predicted correlations (Henseler et al., 2014). Nevertheless, caution is warranted in interpreting model fit indices within the PLS-SEM framework. Hair et al. (2018) emphasize that model fit assessment should be approached conservatively, given that PLS-SEM is primarily designed for prediction-oriented and

exploratory research rather than strict theory testing. Several leading scholars (Ali et al., 2018; Benitez et al., 2020; Sarstedt et al., 2017) have similarly questioned the applicability of traditional model fit indices in PLS-SEM, noting that the method's focus on prediction and variance explanation distinguishes it from covariance-based SEM. Dash and Paul (2021) further argue that overreliance on fit indices may obscure the predictive strengths of PLS-SEM, which should remain the central criterion for evaluation.

Taking these cautions into account, the SRMR results in this study conservatively suggest minimal discrepancies between observed and predicted correlations, thereby supporting the model's capability to capture the underlying relationships among the variables. This interpretation aligns with recent methodological recommendations that emphasize balancing predictive accuracy with cautious use of fit indices (Hair et al., 2023; Sarstedt et al., 2022). Accordingly, the combination of R^2, f^2, Q^2, and SRMR provides a robust assessment of model quality, demonstrating that the conceptual model is both explanatory and predictive in nature. Table 19 reports the detailed results of these assessments, offering evidence of the model's adequacy in capturing the hypothesized relationships.

Table 19

Model Quality of the Conceptual Model

	Saturated Model	Estimated Model
SRMR	0.051	0.051

Source: Author's calculations using primary data.

Chapter Summary

This chapter presented a robust and comprehensive analysis of the data through PLS-SEM. All the five hypotheses were accepted and supported by the analysis of data collected from the questionnaire. Through the PLS-SEM techniques employed in this study, it was revealed that the direct relationship between both doctoral students' well-being and research environment on doctoral students' intention to quit were significant from the quantitative data ($\beta = 0.448$, t = 4.096, $p < 0.05$, CI = [0.239, 0.547]), H2, was supported and ($\beta = 0.447$, t = 5.609, $p = p < 0.05$, CI = [0.262, 0.587]), H4, was supported. Similarly, significant direct relationship was found between research environment and doctoral students' well-being from the quantitative data ($\beta = 0.412$, t = 5.115, $p < 0.05$, CI = [0.258, 0.607]). Thus, H1 was supported. Finally, the indirect relationship between the research environment on doctoral students' intentions to quit mediated by doctoral students' well-being from the quantitative data ($\beta = 0.185$, t = 3.242, $p < 0.05$, CI = [0.091, 0.306]), H3, was supported.

Chapter 5: Presentation of Findings

Introduction

This chapter presents the methodology that was adopted for this study. The objective of this study was to investigate doctoral students' well-being and its antecedents and consequences from the Job Demands-Resources model using quantitative methods. A key aim of this study is to examine the effects of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model as the theoretical basis for this research. A specific goal of this study is to determine the predictive relationship between (1) the research environment as antecedents and (2) the intentions to quit as consequences and doctoral students' well-being using the Job Demands-Resources model.

The current chapter discusses the findings pertaining to the four hypotheses that were developed to address the research questions and finally concludes with the chapter summary.

Job Demands-Resources Literature

The Job Demands-Resources model served as a theoretical framework for this dissertation. This study examined the relationship between research environment and doctoral students' intention to quit as antecedent and consequence of the Job Demands-Resources model, mediated by doctoral students' well-being. In this study, job resources were measured through the construct of research environment, particularly supervision; resources; research community; and professional development. Doctoral students' intention to quit was assessed using the revised scale from Mobley (1977) while doctoral students' well-being was adopted through the MHC-SF to reflect the psychological side

of well-being. Key findings revealed: (1) the quality of the research environment positively predicts doctoral students' psychological well-being, (2) doctoral students' psychological well-being negatively predicts their intentions to quit, (3) the quality of the research environment negatively predicts doctoral students' intention to quit, and (4) psychological well-being mediates the effects of research environment on doctoral students' intention to quit. Notably, policies on enhancing closer supervisory relationship and opportunities for professional development could lower doctoral students' intention to quit. Similarly, ensuring high quality and accessibility of research community and resources also contribute towards lowering doctoral students' intention to quit (Horta et al., 2018; Park et al., 2021).

Research Environment and Doctoral Students' Well-Being

***H1*: The quality of the research environment positively predicts doctoral students' psychological well-being.**

The results of data analysis show that the t-statistic value for the hypothesized relationship of the quality of research environment and doctoral students' psychological well-being was significantly larger than the t-table value (5.115 > 1.96) which means that, according to the self-report of participants in the current study, the quality of the research environment positively predicts doctoral students' psychological well-being. Therefore, H1 is accepted.

As such, the quality of the research environment was a predictor of doctoral students' psychological well-being, with a moderate path coefficient value of 0.412. In line with Job Demands-Resources theory, the current study verified H1, specifically the research environment as a multidimensional construct significantly and positively

predicted doctoral students' psychological well-being. Institutions should invest in structured doctoral support systems that improve supervisory quality, access to resources, and research community engagement. For example, institutions should implement regular supervisory feedback sessions and develop centralized resource portals for doctoral students' administrative and academic support. This is consistent with earlier studies (Jackman & Sisson, 2022; McAlpine & Amundsen, 2012) where having a positive research culture and conditions for improving one's research skills are deemed as key predictors of doctoral students' well-being. This phenomenon was further supported by Jackman et al. (2022) where the quality of the institutional resources was an important predictor of well-being. In a similar vein, Jackman et al. (2022) also posited that the quality of the university facility was an important predictor of well-being. However, this phenomenon contradicts the findings by Mackie and Bates (2019) where they suggested that doctoral students' high stress levels could be partly caused or exacerbated by the supervisory relationship. It also functions as an important antecedent of doctoral students' well-being. The findings of the current study suggest that the quality of the research environment positively predicts doctoral students' psychological well-being. Specifically, the four key aspects of research environment were construed as resources from the perspectives of Job Demands-Resources theory: supervision (the relationship a student has with their supervisor; the availability of a supervisor in providing the student with adequate feedback and guidance); resources (computing amenities' access to students, high-quality books and journals, library facilities, and support financially); research community (the department's intellectual surroundings, that include opportunities for experiencing social interactions, partaking in research ventures, motivating seminars);

and professional development (having the opportunities to build their skills in order to manage projects and to develop professional networks).

Finally, the results indicate that the estimated path coefficient value of 0.412 suggests a direct relationship between the quality of research environment and doctoral students' psychological well-being, specifically for every unit increase in research environment, doctoral students' psychological well-being is expected to increase by 0.412 units. The estimated path coefficient value of 0.412 suggests a moderate effect of the quality of research environment as a predictor variable on doctoral students' psychological well-being as an outcome. The *p*-value was 0.000 which was lower than the significance level of 0.05. Henceforth, H1 was accepted where the quality of research environment positively predicts doctoral students' psychological well-being.

Doctoral Students' Well-Being and Intentions to Quit

***H2*: Doctoral students' psychological well-being negatively predicts their intentions to quit.**

In the current study, the t-statistic value for the hypothesized relationship of doctoral students' psychological well-being and intentions to quit was significantly larger than the t-table value (4.096 > 1.96) which means that the psychological well-being of doctoral students negatively predicts their intentions to quit. Therefore, H2 was accepted.

According to Lyubomirsky et al. (2005), well-being has important downstream consequences such as intentions to quit. While typical doctoral programs begin with structured coursework akin to undergraduate bachelor programs, doctoral students spend majority of their time engaging in unstructured tasks such as literature reviews, data collection, and manuscript work. Such tasks have been previously associated with social,

motivational, and psychological struggles in doctoral students regardless of phases and disciplines (Evans et al., 2018; Lau & Pretorius, 2019; Levecque et al., 2017). Correspondingly, doctoral students often report dealing with social isolation (Litalien & Guay, 2015; McAlpine & Amundsen, 2009), imposter syndrome (Sverdlik et al., 2020), and difficulties balancing academic and personal responsibilities (Brus, 2006; Rizzolo et al., 2016), all of which can cause stress and dissatisfaction among doctoral students leading to intentions to quit (Sverdlik & Hall, 2020). Numerous studies have shown that well-being is associated with various adaptive outcomes such as better performance (Daniels & Harris, 2000; González-Betancor & Dorta-González, 2020; Stubb et al., 2011), health, and social relationships (Kansky, 2017) and dropout intention (Stubb et al., 2011). For doctoral students, two important outcomes might be performance (i.e., grades, thesis project, and research productively) and intentions to quit. Past studies have shown that among doctoral students, those with poor mental health were more likely to think about quitting the program (Almasri et al., 2022). Likewise, González-Betancor and Dorta-González (2020) found that students who have suffered anxiety, depression, or discrimination are more likely to interrupt their doctoral studies. On the contrary, according to Wollast et al. (2023), poor levels of emotional well-being are present among doctoral students particularly among the female candidates and leading to weaker intended doctoral persistence. The result indicates that positive psychological well-being negatively predicted intention to quit (H2). Based on the findings, universities should integrate mental health into doctoral curricula by offering workshops on stress management, mindfulness, and coping strategies. This phenomenon is supported by the findings of other studies (McAlpine et al., 2022). These results are consistent with the

JD-R theory that work engagement and job satisfaction (i.e., positive well-being) have a positive impact on performance outcomes, whereas job exhaustion (i.e., negative well-being) has a negative effect on performance outcomes (Bakker & Demerouti, 2017). The findings of this study contribute to the body of knowledge about the impact of psychological well-being at the doctoral level.

Finally, in the present study the estimated path coefficient value of 0.448 indicates a positive and significant relationship between doctoral students' psychological well-being and intentions to quit, specifically for every unit increase in doctoral students' psychological well-being, doctoral students' intentions to quit is expected to decrease by 0.448 units. An estimated path coefficient value of 0.448 suggests a moderate effect of doctoral students' psychological well-being as a predictor variable on doctoral students' intentions to quit as an outcome. The estimated path coefficient value of 0.448 which was considered as moderate statistically, and similarly the *p*-value is 0.000 which was lower than the significance level of 0.05. Henceforth, H2 was accepted where doctoral students' psychological well-being negatively predicts their intentions to quit.

Research Environment and Intentions to Quit

***H4*: The quality of research environment negatively predicts doctoral students' intentions to quit.**

The results of data analysis show that the t-statistic value for the hypothesized relationship of research environment and doctoral students' intentions to quit was significantly larger than the t-table value (5.906 > 1.96) which means that the quality of the research environment negatively predicts doctoral students' intentions to quit. Therefore, H4 was accepted.

The different aspects of the research environment are conceptualized as job resources under the Job Demands-Resources model and might serve as important antecedents and consequences of doctoral students' well-being and intentions to quit. For this study, the four key aspects of research environment were construed as resources from the perspectives of Job Demands-Resources theory: supervision (the relationship a student has with their supervisor; the availability of a supervisor in providing the student with adequate feedback and guidance); resources (computing amenities' access to students, high-quality books and journals, library facilities, and support financially); research community (the department's intellectual surroundings, that include opportunities for experiencing social interactions, partaking in research ventures, motivating seminars); and professional development (having the opportunities to build their skills in order to manage projects and to develop professional networks). The result of this study suggests that the influence of job resources (i.e., quality of research environment) becomes particularly evident when doctoral students are confronted with high levels of pressure or adversity (Bakker & Demerouti, 2017). One of the key aspects of research environment, particularly supervision, can be interpreted as a form of support that doctoral students receive from their faculty. In organizational behaviour research, perceived organizational support is an important antecedent of employee performance, well-being, and turnover (Rhoades & Eisenberger, 2002). Likewise, sufficient supervision can lead to better performance and lower intentions to quit when doctoral students encounter competitive pressures or research tasks (i.e., negative well-being status). Findings from these studies highlighted that different aspect of research environment have an impact on doctoral students' intention to quit such as heavy

workloads and social conflicts (Kurtz-Costes et al., 2006; Maslach, 2003; Rummell, 2015), conflicts within their scholarly community (Stubb et al., 2011), and difficulties with their advisors (Ellis, 2001). Similarly, supervisors should be trained to recognize the signs of disengagement and proactively support doctoral students. This model represents the relevance of the Job Demands-Resources theory to understand how the availability and adequacy of resources (i.e., research environment) provided to doctoral students may potentially affects their intentions to quit.

Finally, the results indicate that the estimated path coefficient value of 0.446 which indicates a positive and significant relationship between the quality of the research environment and doctoral students' intentions to quit, specifically for every unit increase in the research environment, doctoral students' intentions to quit is expected to decrease by 0.446 units. An estimated path coefficient value of 0.446 suggested a moderate effect of the quality of research environment as a predictor variable on doctoral students' intentions to quit as an outcome. The estimated path coefficient value of 0.446 was considered as moderate statistically, and similarly the *p*-value is 0.000 which was lower than the significance level of 0.05. Henceforth, H4 was accepted where the quality of the research environment negatively predicts doctoral students' intentions to quit.

Research Environment and Intentions to Quit Mediated by Doctoral Students' Well-Being

***H3*: Psychological well-being mediates the effects of the quality of research environment on doctoral students' intentions to quit.**

The results of this study indicate that the quality of research environment and intentions to quit have a significant indirect relationship through the intervening effect of

psychological well-being as $\beta = 0.185$, t = 3.242, $p < 0.05$. Here, the β represents the product of relationships between predictor and mediator (PRES → MHC-SF) and mediator and outcome variable (MHC-SF → MS). In addition, a direct effect of predictor on outcome variable (PRES → MS) was observed which was positive and significant. Therefore, H3 was supported which indicates that there is a mediation effect of doctoral students' well-being on the relationship among predictor and outcome variable (PRES → MS).

The findings further elucidated that quality of the research environment indirectly influence doctoral students' intentions to quit through affecting their psychological well-being. Hereafter, this finding also contributes depth to our understanding of how the quality of the research environment influences the experiences and decisions of doctoral students. Policy reforms are needed to recognize doctoral students' well-being as a strategic lever in the design of doctoral program. This outcome is consistent with existing literature that has studied these constructs under different settings. For example, doctoral students have shown that stress reduces well-being (Moate et al., 2019; Rummell, 2015) and decreases the ability to meet deadlines and complete study-related tasks (Barry et al., 2018). Similarly, dissatisfaction with academia or a particular program of study (Rummell, 2015), faculty members associated with the program (Lovitts, 2002), thesis advisor characteristics (Gill et al., 2012; Godskesen & Kobayashi, 2016; Litalien & Guay, 2015), and aspects of the discipline could all contribute to doctoral student dropout. This result also aligns with the qualitative study by Barry et al. (2018), wherein most students explicitly reported that stress directly delayed their academic progress and ability to complete tasks. The result of the quantitative study by Wollast et al. (2023) also

corroborated with this phenomenon wherein a doctoral candidate works in a well-articulated academic environment (i.e., structure) with opportunities to make choices and take initiatives (i.e., autonomy), the need for a highly involved supervision style becomes less salient for his or her own emotional well-being and thereby affecting the doctoral trajectory. In contradiction, a recent study by Li et al. (2025) revealed that three aspects of the research environment, namely, (1) research culture, (2) skills development, and (3) supervision were not associated with performance and intention to quit through the mediation role of positive well-being.

Finally, the results indicate that the estimated path coefficient value of 0.342 which indicates a positive and significant relationship between the quality of the research environment and doctoral students' intentions to quit mediated by doctoral students' psychological well-being, specifically for every unit increase in the research environment, doctoral students' intentions to quit is expected to decrease by 0.342 units. An estimated path coefficient value of 0.342 suggested a moderate effect of the quality of research environment as a predictor variable on doctoral students' intentions to quit as an outcome. The estimated path coefficient value of 0.342 was considered as moderate statistically, and similarly the *p*-value is 0.001 which was lower than the significance level of 0.05. Henceforth, H3 was accepted which indicates that there is a mediation effect of doctoral students' well-being on the relationship among the quality of the research environment and doctoral students' intention to quit.

Chapter Summary

This chapter presented a detailed discussion of the results of the data analysis. The crux of this study lies with the examination of the effects of research environment as

antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being using the Job Demands-Resources (JD-R) model as the theoretical basis. All four hypotheses were accepted and supported by the analysis of data collected from the questionnaire. The result of the first hypothesis revealed that the quality of research environment positively predicts doctoral students' psychological well-being. Similarly, the second hypothesis was supported by the results wherein doctoral students' psychological well-being negatively predicts their intentions to quit. Thirdly, the result also highlighted that the quality of the research environment negatively predicts doctoral students' intentions to quit. Finally, the fourth hypothesis indicates that there is a mediation effect of doctoral students' well-being on the relationship between the quality of the research environment and doctoral students' intention to quit.

Chapter 6: Conclusion

This dissertation underscores the noteworthy application of Job Demands-Resources (JD-R) theory to examine the effects of the quality of research environment as antecedents and the corresponding consequences such as intentions to quit on doctoral students' well-being. This quantitative, cross-sectional study investigated the complex relationship between various variables such as the quality of research environment, doctoral students' well-being and intention to quit. In addition, the findings of this study contribute to a growing body of literature that highlights the importance in understanding the antecedents and consequences of doctoral students through the Job Demands-Resources (JD-R) model. Self-reported survey data was collected from 278 doctoral students who completed the Postgraduate Research Experience Survey (PRES) (Bennett & Turner, 2013), the Mental Health Continuum-Short Form (MHC-SF) (Keyes, 2009), Intentions to Quit (Mobley, 1977), and provided demographic information including gender, age, doctoral degree type, study year, and discipline area.

The chapter begins with the interpretation of findings derived from the study followed by the examination of the study's limitations and implications. Lastly, the chapter concludes with recommendations for future research and concluding remarks on this study.

Implications

This quantitative correlational study was designed to investigate whether, or to what degree, the antecedents (quality of research environment) affect doctoral students'

well-being leading to consequences such as intention to quit. The findings from this study included numerous significant outcomes that have practical and theoretical implications.

Implications for Education Institutions. The study highlighted the evidence that the quality of research environment was a predictor of doctoral students' psychological well-being, with a moderate path coefficient value of 0.412. The quality of the research environment positively predicts doctoral students' psychological well-being. It is imperative for education institutions to pay attention to maintaining the quality of research environment, specifically, the four key aspects of research environment such as: supervision (the relationship a student has with their supervisor; the availability of a supervisor in providing the student with adequate feedback and guidance); resources (computing amenities' access to students, high-quality books and journals, library facilities, and support financially); research community (the department's intellectual surroundings, that include opportunities for experiencing social interactions, partaking in research ventures, motivating seminars); and professional development (having the opportunities to build their skills in order to manage projects and to develop professional networks). These aspects of research environment serve as important antecedent to doctoral students' well-being. Similarly, it was proven in this study that the quality of the research environment negatively predicts doctoral students' intentions to quit. In particular, the influence of job resources (i.e., quality of research environment) becomes evident when doctoral students are confronted with high levels of pressure or adversity which may influence doctoral students' intention to quit. The result of this study also supported the hypothesis that psychological well-being of doctoral students negatively predicts their intentions to quit. Past studies have also shown that among doctoral

students, those with poor mental health were more likely to think about quitting the program (Almasri et al., 2022). Therefore, it is timely and apt for the education institutions to explore strategies and interventions in improving mental health conditions as well as holistic well-being of doctoral students. Lastly, the result of this study revealed that the quality of research environment and intentions to quit have a significant indirect relationship through the intervening effect of psychological well-being. For example, doctoral students have shown that stress reduces well-being (Moate et al., 2019; Rummell, 2015) and decreases the ability to meet deadlines and complete study-related tasks (Barry et al., 2018) could all contribute to doctoral student dropout. Thus, it is apparent that education institutions not only need to maintain the quality of the research environment but also pay attention to the well-being of doctoral students, specifically the psychological well-being. The study has important implications not only for stimulating awareness of doctoral students' well-being but also offers useful insights for administrators on which aspects of the research environment need to be targeted to enhance PhD students' well-being and performance.

Theoretical Implications. This study is an application of the Job Demands-Resources (JDR) theory to the context of doctoral students' well-being and intention to quit. The contribution to the literature is two-fold, one is to the literature on Job Demands-Resources (JD-R) theory, and two is the application of Job Demands-Resources (JD-R) theory in understanding doctoral students' well-being and intention to quit. In a competitive and worldwide higher education structure, this study offers vital knowledge and be of assistance to higher education institutions around the world and to assist them in deliberately focusing on their policies, programs, and strategies for the

encouragement and nurturing of their doctoral students' well-being. Furthermore, the findings from this study offer a nuanced appreciation of how the quality of research environment as the antecedent affects doctoral students' well-being thereby affecting their intentions to quit. Finally, this study contributes a unique perspective on Job Demands-Resources (JD-R) theory, doctoral students' well-being, and intentions to quit in the higher education context.

Limitations of the Study

While this study provides invaluable insights into understanding how the quality of research environment and doctoral students' well-being influences doctoral students' decisions, it is fundamental to acknowledge the inherent limitations. Limitations are not uncommon in quantitative research and belong to an aspect within the study that researchers recognize as having potential negative impact on the research outcomes (Gay et al., 2012).

First, the relationships among the constructs identified in this study may be temporary linkages as these were identified based on the cross-sectional dataset. Therefore, the findings of this study may not be claimed for causality. Instead, the findings confirmed that associations are indeed present. In addition, potential confounding variables were not adequately considered when examining the relationships between the studied constructs. Furthermore, such methods can overlook individuals nuanced, contextual experiences that define their understanding and perceptions of a phenomenon (Beglaryan & Sargsyan, 2023).

PLS-SEM also presented inherent limitations. While PLS-SEM is well-suited for exploratory studies with complex relationships, it does not provide a goodness-of-fit

measure commonly available in covariance-based SEM methods (Hair et al., 2020). It is essential to have an excellent fit to assess the model's adequacy fully. When this does not happen, the results become more challenging to interpret. Studies that use a fitted model as a foundation for conclusions should be especially concerned about this issue.

Another limitation is the assumption that the participants' responses to survey questions are truthful. This assumption rests upon the participants' trust in the anonymity and confidentiality of the study. The questionnaire was distributed online using Google Forms as the only survey avenue for participants to complete the questionnaire. Even with efforts to ensure confidentiality, the possibility of biased responses exists in any research relying on self- reported data.

While this study uses simple random sampling (Ahmad et al., 2023) to reduce the potential for sampling bias, which emerges if the sample is not representative of the broader population and cannot apply to groups not included in the study, affecting the generalizability of the study. The reliance on LinkedIn as the digital platform for recruiting participants introduces self-selection bias. Self-selection bias occurs since the respondents recruit themselves into the survey, rather than being selected (Baker et al., 2010; Kohler, Kreuter, & Stuart, 2019; Mercer et al., 2017). This leads to biased estimates if a variable is correlated with the outcome variable and the response propensity, respectively (Groves, 2006; Mercer et al., 2017).

Recommendations for Future Research

The significance and implications of doctoral students' well-being was once again illuminated by the findings of this study. Specifically, there are two recommendations for

future researchers to consider when carrying out research relating to doctoral students' well-being.

This research evaluated doctoral students' perceptions and views at a specific timestamp which may be affected by the larger environment. However, it was emphasized by Venkatesh and Brown (2001) that people's perception will change over time, as their experiences deepen. Therefore, future researchers should consider the conduct of longitudinal studies to gain insights into how employees' perceptions and preferences may develop over time. Similarly, to overcome the shortcoming of cross-sectional research design, future researchers may use a longitudinal or experimental study to explore causal relationships and consider controlling for covariance.

While this study's quantitative design provided valuable insights into the relationships between antecedents and consequences of doctoral students' well-being using the Job Demands-Resources model, qualitative methods could uncover nuanced perspectives on doctoral students' intention to quit (Beglaryan & Sargsyan, 2023). One way to conduct qualitative research might be to conduct in-depth interviews with doctoral students to glean insights into their respective doctoral journey. Such interviews could elicit rich details about the kinds of contextual challenges these doctoral students face and the interventions that helped them build confidence in completing this journey. In addition to interviews, a mixed-methods survey would provide a clearer picture of the factors affecting doctoral students' intention to quit.

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Appendix 1

Completion Certificate for IRB Training

Figure 5

Lesson 1: When HHS Regulations Apply



Congratulations!

You have completed OHRP's learning module:

Lesson 1: When HHS Regulations Apply

OHRP does not collect information about who completes this training. Please fill out the information below and print this page for your records.

Name: Guo Qiang TAN

Date: 29/12/2024

Figure 6

Lesson 2: What is Human Subjects Research?



Congratulations!

You have completed OHRP's learning module:

Lesson 2: What is Human Subjects Research?

OHRP does not collect information about who completes this training. Please fill out the information below and print this page for your records.

Name: Guo Qiang TAN

Date: 29/12/2024

Figure 7

Lesson 3: What are IRBs?



Congratulations!

You have completed OHRP's learning module:

Lesson 3: What are IRBs?

OHRP does not collect information about who completes this training. Please fill out the information below and print this page for your records.

Name: Guo Qiang TAN

Date: 29/12/2024

Figure 8

Lesson 4: Independent Review of Research



Congratulations!

You have completed OHRP's learning module:

Lesson 4: Independent Review of Research

OHRP does not collect information about who completes this training. Please fill out the information below and print this page for your records.

Name: Guo Qiang TAN

Date: 29/12/2024

Figure 9

Lesson 5: Human Research Protection Training



Congratulations!

You have completed OHRP's learning module:

Lesson 5: Human Research Protection Training

OHRP does not collect information about who completes this training. Please fill out the information below and print this page for your records.

Name: Guo Qiang TAN

Date: 29/12/2024

Appendix 2

Survey: Investigating the effects of doctoral students' well-being and their antecedents and consequences from a Job Demands-Resources perspective

Estimated time: ~20 minutes Total items: 33

Researcher: Dr. Tan Guo Qiang

Purpose: To examine how institutional and supervisory support influence doctoral students' well-being and how well-being affects academic performance and dropout intentions.

Data Use & Ethics

- Your responses are confidential and anonymous.
- Data will be securely stored and deleted after 3 years.
- Participation is voluntary, and you may withdraw at any time.

Section A: Informed Consent & Demographics

1. Informed Consent *

   Mark only one oval.

   ◯ Yes, I agree to participate in this study.

   ◯ No, I do not wish to participate.

2. Gender *

Mark only one oval.

- ◯ Male
- ◯ Female
- ◯ Non-binary / third gender
- ◯ Prefer not to say

3. Age *

Mark only one oval.

- ◯ <25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ >55

4. Doctoral Degree Type *

Mark only one oval.

- ◯ PhD degree
- ◯ Professional Doctorate (e.g., DBA, EdD)

5. Study Year *

Mark only one oval.

- ◯ Year 1
- ◯ Year 2
- ◯ Year 3
- ◯ Year 4
- ◯ Year 5 or above

6. Discipline Area *

Mark only one oval.

- ◯ Humanities
- ◯ Science/Engineering
- ◯ Business/Professions

Section B: Research Environment (Adapted PRES, 6 items)

7. My supervisor(s) have the skills to support my research *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

8. I receive timely and constructive feedback from my supervisor(s). *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

9. My university provides the necessary research facilities and resources (e.g., labs, software, databases). *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

10. I have sufficient access to academic seminars, training, and workshops. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

11. I have opportunities to collaborate with fellow researchers. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

12. I feel that the research environment promotes academic growth. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

Section C: Psychological Well-Being (MHC-SF, 6 items)

13. During the past month, how often did you feel happy. *

Mark only one oval.

- ◯ Never
- ◯ Once or twice
- ◯ About once a week
- ◯ 2 or 3 times a week
- ◯ Almost every day
- ◯ Every day

14. During the past month, how often did you feel that you had something important to contribute to society. *

Mark only one oval.

- ◯ Never
- ◯ Once or twice
- ◯ About once a week
- ◯ 2 or 3 times a week
- ◯ Almost every day
- ◯ Every day

15. During the past month, how often did you feel satisfied with life. *

Mark only one oval.

- ◯ Never
- ◯ Once or twice
- ◯ About once a week
- ◯ 2 or 3 times a week
- ◯ Almost every day
- ◯ Every day

16. During the past month, how often did you feel a sense of belonging to a community. *

Mark only one oval.

- ◯ Never
- ◯ Once or twice
- ◯ About once a week

- 2 or 3 times a week
- Almost every day
- Every day

17. During the past month, how often did you feel that you could handle daily responsibilities well. *

Mark only one oval.

- Never
- Once or twice
- About once a week
- 2 or 3 times a week
- Almost every day
- Every day

18. During the past month, how often did you feel motivated and optimistic about your research journey. *

Mark only one oval.

- Never
- Once or twice
- About once a week
- 2 or 3 times a week
- Almost every day
- Every day

Section D: Performance & Intentions to Quit (Mobley + SRP, 6 items)

19. I am satisfied with my academic performance over the last month. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

20. I feel I am making good progress on my doctoral thesis. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

21. I have considered dropping out of my doctoral program. *

Mark only one oval.

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

22. I frequently think about alternative career or education options. *

Mark only one oval.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

23. If I were offered a different academic or professional opportunity, I would likely leave this program. *

Mark only one oval.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree

24. I feel confident that I will complete my doctoral degree. *

Mark only one oval.

- Strongly disagree
- Disagree
- Neither agree nor disagree
- Agree
- Strongly agree