Use of Wearable Sensors to Unveil Roles of Task Demands-Personal Resources and Burnout on Performance of Construction Workers

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Abstract

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This dissertation examines how task demands and personal resources affect construction workers' productivity and safety performance. Additionally, the paper investigates the existence of a mediating mechanism of burnout in the relationship between job characteristics and workers' performance. Through a quasi-experimental study, a modified "Job demands-resources model (JD-R)" for construction workers is validated at the task and individual levels. The modified model extends the discussion from job characteristics to performance consequences. In accordance with the Oldenburg Burnout Inventory, the model was designed to measure burnout by considering the two dimensions of exhaustion and disengagement in the context of construction workers from the non-service work category.

The 22 subjects in the quasi-experiment comprised trainees in a pre-apprenticeship program and university students. They participated in multiple experiments that were designed to expose subjects to different levels of task demands and record different levels of personal resources; the final dataset for data analysis included 80 observations. Owing to the limited sample size and the explanatory nature of this dissertation research, the proposed model consists of indirect paths from task demands and personal resources to performance outcomes, and hypothesis testing is performed by applying partial least squares structural equation modeling (PLS-SEM). The mediation effect of exhaustion and disengagement was analyzed after including the direct path in the revised model, and utilizing only the significant paths among the indirect paths from task demands and personal resources to productivity and safety performance outcomes.

The results indicate that exhaustion and disengagement have different relationships with performance outcomes. High burnout (exhaustion) and low disengagement (high engagement) subjects showed high productivity levels but low safety performance. Thus, there is a greater possibility that exhausted workers, who are depleted of mental and physical energy, will fail to comply with ergonomic safety, either intentionally or unintentionally. The combined model mixed survey and survey measurements results in a better overall predictive performance for the exogenous constructs than the model that only used either survey measurements or sensor measurements. Thus, the findings suggest that that a human factors measurement method cannot replace another. Application of both survey and sensor measurements to human factor variables in the JD-R, burnout, and performance models is necessary for scientific construction workforce management in the construction industry.

The dissertation contributes to the research stream in various ways. The key contribution of this dissertation research is the use of a scientific approach to evaluate construction workers' physical strain and psychological stress. Further, it assesses the effects of such phenomena on their task- and individual-level performance. The study includes and measures both productivity and safety performances to provide insights to improve them and unveil the interrelated mechanism between productivity and safety, which have been discussed separately in prior studies. Specifically, the study measures the unique characteristics of construction performance on the two dimensions of safety (specifically ergonomic safety) and productivity and examines the daily (acute) burnout at the individual and task levels. Second, the study illustrates how the individual-level JD-R and burnout research can be conducted in the construction industry. The JD-R has been applied to a variety of industries, but not in contexts covering both safety and productivity in the construction industry. Indeed, this study increased the understanding of dynamics between safety and productivity. Third, the study extensively uses and uniquely describes the methodology applications of wearable sensors, including physiological status monitors and activity/sleep trackers for construction workforce management research, and the application of PLS-SEM, an emerging tool in management research. By doing this, this dissertation provides detailed theoretical and managerial implications and also a discussion on the scope of future studies.

Table of Contents

Table of Figures

Table of Tables

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Chapter 1 Introduction

1.1 Research Background

Industry and research in built environments have made considerable investments of time and effort to improve user satisfaction with buildings and infrastructure. Understanding how built environments are closely connected to the human body's functioning mechanisms is important when designing comfortable, beautiful, and healthy living places. Le Corbusier, a Swiss-French architect, who is considered as one of the greatest modern architects, introduced modern building-design principles, including the five points of architecture, which are: (1) pilotis, (2) free designing of the ground plan, (3) free design of façade, (4) horizontal window, and (5) roof gardens. Today, these five points are all remain the main basic principles of building designs. Le Corbusier also introduced a human's body scale called the *Modulor* as a basic guideline to design built environments with a golden ratio in human proportions in order to explore human beings for the scale of architectural proportion (Corbusier, 2004). The concept of the *Modulor* involves the use of anthropometry (i.e., body measurements) for designing and producing a built environment in mass production with a standardized building unit. As part of the big theme for contemporary built environments, the *Modulor* simulates the human body proportionally in relationship to its interaction with the building's physical and functional uses. It has been a key research theme for a long period of time for building scientists to investigate a building occupant's physiological and psychological feedback on the thermal condition to develop an empirical model of thermal adaptation in the built environments (Brager & De Dear, 1998). Human activities are executed in a building system where humans interact so that efficient, safe, and comfortable living spaces are determined by built environments in an ergonomic approach (Attaianese & Duca, 2012). For an architect, the understanding of the human perception is important to design a successful lighting system in built environments (Lechner, 2014). Thus, human factors are the center of interest for the design of delightful residential living and working spaces.

There have been prolific considerations for the well-being of the residents and office workers in built environments. Ironically, front-line workers in the construction industry who contribute to creating affordable built environments, have suffered from the exposures to hazardous working environments and health risks. Once workers are recruited, the nature of construction exposes them to highly adverse health effects. The construction industry has recorded one of the highest rates of occupational fatalities and injuries in the United States of America (the U.S.). In terms of industry trends in the U.S., the construction industry had higher fatal occupational injuries rates than the overall manufacturing industry in 2016 (Bureau of Labor Statistics, 2017a). There was a total of 4,836 fatal industrial accidents in the U.S., and the construction industry accounted for 20% of the total in 2015 (Center for Construction Research and Training, 2018). As reported in the Construction Chart Book (Center for Construction Research and Training, 2018), the construction industry also contributed to 134.8 per 10,000 full-time equivalent workers (FTEs) rate of non-fatal injuries resulting in days away from work which is 44% higher than the average of all private industries in 2015. According to the International Labour Organization (2009), deaths on construction sites by accident are three to four times higher than other work sites in industrialized countries. Besides contact with objects, falls, slops, and trips, overexertion in lifting or lowering were some of the primary causes of occupational injuries in the construction industry in 2016 (Bureau of Labor Statistics, 2017b). Previous studies have identified workers' accumulated fatigue originating from continuous work activity, bodily overexertion, or repetitive motion as some of the causes of safety accidents and work-related musculoskeletal disorders (Everett, 1999; Putz-

Anderson et al., 1997). High fatigue and overexertion among workers are also known to be associated with labor productivity, work efficiency, attentiveness, and errors (Abdelhamid & Everett, 2002; Åstrand, Rodahl, Dahl, & StrØmme, 2003; Bernold & AbouRizk, 2010). Overall, increases in physical strain and stress are expected to decrease work productivity (Bernold & AbouRizk, 2010; Ringen, Englund, Welch, Weeks, & Seegal, 1995) and have a negative influence on safe work behavior due to increased distractions and fatigue among workers (Hallowell, 2010).

The competitive nature of the construction industry forces employers to keep wages low. As a result, individuals with lower educational achievements accounted for a large majority of the construction workforce. In addition to low educational attainment, many construction workers have unhealthy behaviors, including poor eating, physical fitness, or sleep habits (Powell & Copping, 2010). Adding shift workers is also a common practice that construction contractors use to accelerate project schedules (Hanna, Chang, Sullivan, & Lackney, 2008). Shift workers, who are commonly added to deal with labor shortages in the construction practice, were found to suffer from a cumulative lack of sleep which affected their circadian rhythms and is associated with lower performance (Tilley, Wilkinson, Warren, Watson, & Drud, 1982). Powell and Copping (2010) found that sleep deprivation elevates an individual's level of fatigue and risk of accidents. In addition, smoking, obesity, diabetes and high blood pressure are also major health-risk factors for construction workers (Center for Construction Research and Training, 2018). Exposures to hazardous chemicals (Verma, Kurtz, Sahai, & Finkelstein, 2003) and exposures to noises (Suter, 2002), all create health risks for construction workers.

The U.S. government has strict labor regulations and injunctions during disputes between employers and labor unions over health and safety issues as well as improving worker's social rights. This has caused an increase in the occupational safety performance of construction companies. These regulations and rights of workers to a safe and healthy workplace was established by the Occupational Safety and Health Administration (OSHA). Employers are requested to comply with the OSHA standards to keep employees safe from recognized hazards. Despite this effort to establish workers' safety, according to the Bureau of Labor Statistics (2017c), the number of fatal occupational injuries in the U.S. construction industry is still high in comparison to those in other industries. From a project manager's perspective, the pressure to achieve high monetary profits by reducing scheduling is more crucial than any other managerial issue. In addition, an organizational culture that primarily emphasizes on the results over means often exposes workers to risks that increase accident and injury rates (Flin, Mearns, O'Connor, & Bryden, 2000; Maudgalya, Genaidy, & Shell, 2008).

Productivity measured by the number of completed units for the input man-hour of work is used as an indicator of the most generally quantitative performance reporting in the construction industry (Cox, Issa, & Ahrens, 2003). Over the last few decades, with a few exceptions, labor productivity has continued to be on a slow steady decline (Sveikauskas, Rowe, Mildenberger, Price, & Young, 2014; Teicholz, Goodrum, & Haas, 2001). Hanna, Taylor, and Sullivan (2005) confirmed the effect of decreasing productivity due to fatigue and the reduction of synchronization during overtime, and labor cost. Hanna et al. (2008) pointed out that there is a positive relationship between the percentage of shift work (Total shift work manhours/ Total the budgeted labor hours for project) and the productivity loss. Hanna et al. (2008) also reported that the shift worker's disturbance of normal sleeping hours may have adverse effect on safety. Jarkas and Bitar (2012) found that human/labor factors, such as motivation of labor, skill of labor, physical fatigue, and level of experience influence labor productivity.

While research on the effect of human factors on productivity and safety is still largely based on the perception of workers, a variety of sensor application studies have recently been conducted to objectively measure these factors. Alwasel, Abdel-Rahman, Haas, and Lee (2017) measured human factors, such as posture and muscle compression, using sensors to investigate the effect of workers' experience on productivity and ergonomics risk in masonry work. The micro-motion level of human factors on material-handling activities, such as the distance from hand to object while lifting and lowering, grip type, and material weight, were investigated to evaluate its impact on the efficiency of the plate handling task (Golabchi, Han, AbouRizk, & Kanerva, 2016). Cheng, Teizer, Migliaccio, & Gatti (2013) introduced an activity status reasoning method through fusion with a worker's thoracic posture data obtained from accelerometer sensor, in addition to an automatic work sampling method using real-time location sensing. Gatti, Migliaccio, Bogus, and Schneider (2014) quantified the physical strain of a worker through the physiological status monitors system by measuring the heart rate and breathing rate, in addition to studying the relationship with productivity.

A myriad of variables that affect safety performance and the causal relations of these variables are intertwined. Fang, Jiang, Zhang, and Wang (2015) found that there is a negative correlation between a subject's fatigue level and safety performance for a material handling task experiment conducted with 20 male rebar workers. Based on interviews on construction managers and safety managers, Poon, Rowlinson, Koh, and Deng (2013) found that fatigue has a direct adverse effect on safety performance. Poon et al. (2013) also found mediating factors such as under-evaluation of contribution from safety personnel, rivalry and political maneuvering, and mechanistic application of the safety management system has an adverse effect on the relationship between job burnout and safety performance. One-third of workers reported their jobs to be a source of stress (National Institute for Occupational Safety and Health, 1999). With growing evidence, job stress plays a significant role in causing major health problems, such as cardiovascular disease, psychological disorders, and musculoskeletal disorders (National Institute for Occupational Safety and Health, 1999). If job demands do not match a worker's capabilities, needs, or resources, the worker is likely to incur job stress as a harmful physical and psychological response (National Institute for Occupational Safety and Health, 1999). Based on the National Institute for Occupational Safety and Health (NIOSH) model of job stress and health (Hurrell & McLaney, 1988), a mitigation plan should simultaneously focus on both the workers and the working environment/conditions. As a tool of objective measurement for monitoring and collecting information on human factors which influence a worker's productivity and safety performance, wearable technologies are considered to have significant potential (Awolusi, Marks, & Hallowell, 2018; Joshua & Varghese, 2010). The recent and rapid development of wearable sensors and mobile computing technology has considerably contributed to the methods of collecting data (Chaffin et al., 2017). In particular, improvements in bio-sensing technology would enable scientific management research by providing non-invasive methods to measure workers' physiological variables. Utilizing novel monitoring technologies that were introduced by medical instruments, sports medicine, and data science vendors provides rich data on risk factors that can affect both worker productivity and safety.

According to a report published by the McKinsey Global Institute (Manyika et al., 2015), the economic value of the Internet of Things (IoT) technology application on worksites will be up to

930 billion dollars per year in 2025, as the IoT can benefit optimizing operation, save costs from accidents, and improve productivity. Manyika et al. (2015) also predicts that the value of applying wearable technologies in business management will be more for business-to-business services of the IoT application in comparison to the general consumer product use. In the current commercial market, many wearable technologies are pervasive and garnering more attention by construction industry. Feasibility, usability tests, and investigation of technology acceptance by project managers and front-line workers to make wearable IoT technology, such as activity/motion tracker, physiological monitor, and location tracker, more applicable in construction practice have also been conducted by researchers in the construction engineering and management areas (Choi, Hwang, & Lee, 2017; Guo, Yu, Xiang, Li, & Zhang, 2017; Lee, Lin, Seto, & Migliaccio, 2017a; Yang, Ahn, Vuran, & Kim, 2017). To make the use of wearable technology application more feasible, the nature of work and the industry should be considered. For instance, construction workers are required to have a safety harness, a fall protection gear, and tool belts, when the relevant hazards to be protected from the personal protective equipment present. Thus, finding optimal placement of sensors is crucial as Lee, Seto, Lin, and Migliaccio (2017b) described. Sensor technology is getting compact and includes combined multiple sensors to monitor several physiological and activity data together. This trend is beneficial for the practical application of technology in the construction industry.

1.2 Problem Statement

The median ages of the workforce have gradually increased in the construction industry from 2011 to 2017 (Bureau of Labor Statistics, 2018). Aged construction workers are more likely to be associated with higher injury cost due to increased hospitalization, lost work days, disability, and so forth (Schwatka, Butler, & Rosecrance, 2012). Ongoing and impending retirements are also making the construction industry suffer from a shortage of skilled and experienced workers, particularly after the recovery from the economic recession (McGraw-Hill Construction, 2012). The construction industry still struggles to attract new young workers and mitigate the ongoing talent shortage (World Economic Forum, 2018). Hence, human resource management in construction is even more important than before to ensure full capacity in optimal working environments and healthy conditions. Construction engineering and management research studies both recognize the emerging problems, and attempt to solve certain issues of occupational safety, health, and productivity in construction. However, etiologic studies on topics of construction productivity, safety, health, and well-being have not been well intermingled and tested in a validated research model. Efforts of existing studies (e.g., Gatti et al., 2014) made contributions in understanding micro-organizational behaviors in the construction industry; however, the studies limitedly addressed the etiologies and associations between two or three segmented factors, even though every factor is interrelated with worker's productivity, safety, and health.

According to a field study with construction roofers undertaken by Lee et al. (2017a), it was found that wearable technology is not entirely comfortable to wear, and the workers were concerned about privacy issues due to the tracking feature in wearable sensors. For instance, some construction workers reported that they were not favorable to wearing the activity tracker and physiological status monitor as they felt that their privacy was invaded during a pilot test (Lee et al., 2017a). Rather than providing sensors to workers and tracking them every day, 24/7, Lee et al. (2017a) proposed a way to minimize the period of data collection. They noted that 3 days of data collection would suffice to obtain reliable data of workers' onsite physiological and activity data.

Besides the feasibility and usability of wearable sensors, a more important aspect is how the data can be used for managerial implications, that is, how and where the data collected by wearable technologies can be employed still need to be investigated.

1.3 Research Scope

To define a general research strategy, it is important to define a construction worker's job characteristics. Based on Karasek and Theorell's (1990) quadrant analysis of the job characteristics of 38 occupants, a construction laborer is placed in the low-decision latitude level. It means construction laborers generally have low freedom to make own decisions when performing their tasks. A construction laborer is positioned near the mean value (but lower than mean) of the level of psychological demands in the demand/control quadrant presented by Karasek and Theorell (1990, pp. 43), while their decision latitude is lower than the other occupations. Furthermore, construction laborers are also positioned near the mean value (but lower than mean) of the level of social support with a low decision latitude based on the demand/control quadrant for the occupational distribution of social support and decision latitude (Karasek & Theorell, 1990, pp.73). A noticeable finding (by the perspective of the current research) in the quadrant analysis for the occupational distribution of physical exertion and decision latitude is that a construction laborer is positioned at the utmost level of physical exertion with low decision latitude (Karasek & Therorell, 1990, pp 67). Thus, this finding encourages this current study to focus on the job characteristics of construction laborers by applying the highest level of physical exertion and low decision latitude. The high level of job strain leads to the risk of physical illness and psychological strain (Karasek, 1979). Subsequent to the industrial revolution, psychological demands replaced physical exertion in many occupations (Karasek & Therorell, 1990). However, overexertion and bodily reactions is still a leading cause of work-related injuries among construction workers (Center for Construction Research and Training, 2018).

Among worker's non-fatal injuries, overexertion and work-related musculoskeletal disorders (WMSDs) are prevalent in the U.S. construction industry (Center for Construction Research and Training, 2018), which are also known to lead to lost or restricted work time due to days away from work. In the U.S. construction industry, the Center for Construction Research and Training (2018) reported the rate of overexertion injuries are highest in (1) finish carpentry and (2) tile and terrazzo (ranking tied) in 2015. Even though there has been a significant decrease in the rate of WMSDs from 1992 to 2015, the total rate per 10,000 full time equivalent employees was higher than the average of all industries based on the data reported in 2015 (Center for Construction Research and Training, 2018). The state level statistics and reports in the U.S. have also specified WMSDs to be the primary cause of non-fatal injuries in the construction industry. The number of compensable WMSDs claims rates in the Washington State construction industry was approximately 50% higher than the rate of manufacturing or healthcare industry in 2010 (Ninica, Bao, Lin, Hunter, & Hass, 2016). WMSDs in back, shoulder, hand/wrist, and elbow were the most common symptoms reported by the Washington State construction workers study (Ninica et al., 2016). Wang, Dai, and Ning (2015) reported the severity of WMSDs due to impairment between worker's ability to perform his/her jobs in West Virginia based on the reported higher rate of WMSDs in the construction industry. Thus, this current dissertation research focuses on the risk of WMSDs among various safety risks leading to incidents, injuries, and near misses.

The following lists are characteristics of construction labors reflected in the proposed research model. I consider the construction laborer's: (1) physical workload assigned, (2) low mental workload contrasted with office workers, (3) low creativity needed while completing the assigned task, (4) physical and mental dimensions combined and acting as mediators, leveraging the job demands and resources, and (5) restrictions on autonomy at task level. These job characteristics for construction laborers ultimately determine the scope of model testing. The new approach to the existing job characteristics and performance research model should be necessary for the management of the construction workforce (construction laborers) as the construction industry is known to be remarkably different from other types of manufacturing industries in terms of its safety extent and health risks (Ringen et al., 1995).

1.4 Structure of the Dissertation

This dissertation is structured into seven chapters. Chapter 1 describes the background, problem statement, and scope of the dissertation research. Chapter 2 reviews the theory of the dissertation research, and summarizes the research questions and objectives. Chapter 3 introduces the research methodology, including the building of hypotheses models, operationalizing constructs, and tools for data collection. Chapter 4 describes the selection of appropriate data analysis method and its application for hypothesis testing. Chapter 5 summarizes the results of data analysis about how task demands and personal resources affect construction workers' performance. It also includes the results of hypotheses testing and provides a prediction performance of the suggested theoretical Job demands-resources (JD-R) and burnout model for construction workforce management. Chapter 6 discusses the outcomes and findings, and presents the direction for future research. The last chapter, Chapter 7, describes the conclusions of the dissertation research. Together, this dissertation illuminates a method for applying wearable sensors to human-resource management in the field of construction. The key contribution of this dissertation study is a scientific approach to evaluate construction workers' physical strain and psychological stress, in order to assess the effects of such phenomena on task and individual-level performance.

Chapter 2 Theory and Literature Reviews

This chapter reviews relevant theory and literature that contribute to the proposed research model that will be presented in the next chapter of this dissertation. Section 2.1 summarizes previously investigated research models and findings regarding job stress, burnout, and performance. Section 2.2 lists the research questions of the current study based on problem statements that the authors found from the literature that was investigated. Section 2.3 presents the objectives of the current research.

2.1 Job Stress, Burnout, and Performance

Karasek and Theorall (1990) proposed the demand-control model of job stress, which describes whether employees can control their job-stress level by leveraging the degrees of job demand and job-decision latitude (e.g., decision authority or skill level). Karasek and Theorall illustrated that as the gap between job demands and decision latitude increases (especially when the job demands are high and the decision latitude is low), the worker's job strain tends to increase as well. This model recommended increasing job-decision latitude through skill training and empowerment to decrease the job-stress level resulting from excessive job demands placed on a given worker. This model was identified to understand the interaction effect between job demands and the level of job control over execution of tasks (i.e., decision latitude) to predict a worker's stress level. However, this model is not broad enough to allow for an understanding of the relationship between job characteristics and the variations of job performance as a consequence of the mismatch between the degree of control and the demand.

The job-stress and health model, which was introduced by Hurrell (1987), indicated that job stressors fostered by job characteristics can lead to negative health outcomes, and individual factors moderate this relationship. Since the result of job stressors in the job-stress and health model consists of illnesses such as hypertension, alcoholism, and mental illness, the model is not broad enough to explain which factors lead to a higher worker performance, as this dissertation research intends to investigate. To observe the illness-related consequences resulting from job stressors and the mediating effects of individual factors on acute reactions, workers will need to be exposed to the stressors for a longer period of time. However, this dissertation research examines the relationship between job stressors and health (e.g., perceived individual health status or fitness to task) during a period of time when workers are under high stress in their roles, and the effects of this stress on daily (acute) burnout. For the non-clinical population, the level of burnout can vary on a daily basis; however, very little is known about the mechanism of daily burnout (Xanthopoulou & Meier, 2014). Existing investigations regarding specific burnout coping strategies on the individual level are limited (Demerouti, 2014). Thus, I identified health status as one of the important personal resources (i.e., individual factors) that allow construction workers to bear physically demanding jobs while maintaining a lower chance of burnout, which in turn produces better job performance.

While the two models discussed previously did not reflect the construction workers' job characteristics, the task-capability interface (TCI) model introduced by Mitropoulos, Cupido, and Namboodiri (2009) is one of the first approaches to understanding the causes of accidents and injuries in the construction industry through a well-validated research model. The TCI model illustrates that an individual's control of demands and resources is a predictor of potential accidents, specifically in the construction industry. This model introduced factors other than decision latitude to control high task demands such as physical characteristics, skill, and experience and training. The model introduced the proposition that dynamic construction activities and the effects of teamwork practices on task demands and applied capabilities in turn influence safety. The TCI model was validated with empirical data (Mitropoulos & Cupido, 2009); however, the data for the variables of task demands and capability were obtained through interviews and observations. Further investigation is needed with variables measured more objectively in order to obtain a detailed understanding of the control mechanism between task demands and capability which leads to potential accidents.

Maslach and Jackson (1981) introduced the concept of job burnout to explain how a worker experiences stress through three dimensions of physical and psychosocial scales, and to detail the antecedents and consequences of the burnout. Maslach's theory defined burnout as a syndrome of emotional exhaustion, depersonalization (e.g., detached and cynical reposes to the recipients of service or care), and reduced personal accomplishment that can occur among human services workers (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). Maslach Burnout Inventory (MBI) was developed to measure these three dimensions of burnout and Maslach's definition of burnout constrains to the syndrome among human services workers; in other words, it restricts the MBI-Human services survey to professionals who work in jobs that primarily consist of treating people other than things or information (Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986). Thus, an MBI-educators survey was developed to measure the burnout subscales for educators (Maslach, Schaufeli, & Leiter, 2001), and Schaufeli, Leiter, Maslach, and Jackson (1997) designed an MBI-general survey for workers engaged in occupations other than human services and education. Maslach et al. (2001) introduced important outcomes of burnout on job performance and health.

Previous research emphasizes that health can also be considered an antecedent of burnout, especially for workers performing physically demanding tasks. Health is an important job resource according to presenteeism and absenteeism research (Meerding, IJzelenberg, Koopmanschap, Severens, & Burdorf, 2005). Workers in America who suffered from sleep disorders have issues of work-related impairments that are eventually associated with a deterioration of their work performance (Swanson et al., 2011). A study conducted by Martimo et al. (2009) found that clinically diagnosed upper extremity disorders among the Finnish working population were associated with a loss of productivity at work. These findings were adopted from the Total Worker Health® (TWH) approach, introduced by the National Institute for Occupational Safety and Health (NIOSH) in 2011. Total worker health is defined as follows:

> "A Total Worker Health® (TWH) approach is defined as policies, programs, and practices that integrate protection from work-related safety and health hazards with promotion of injury and illness prevention efforts to advance worker well-being." (Schill & Chosewood, 2016, p. 4).

Thus, the worker's well-being (e.g., sleep quality) and fitness for duty is linked with promoting the worker's cognitive and behavioral risk safety and productivity (e.g., presenteeism and absenteeism). Burnout syndrome of employees is the main cause of presenteeism in many occupations (Bakker & Costa, 2014; Demerouti, Le Blanc, Bakker, Schaufeli, & Hox, 2009). Understanding presenteeism is more crucial than understanding absenteeism for the prevention of loss of productivity, which is difficult to observe and measure. Anger et al. (2015) provided propositions in an overview of the TWH, which asserted that validation of the TWH concept through the research model is needed in order to promote the TWH concept for application to both individuals and organizations. Only a few research evaluations of the underlying process of TWH have been conducted (Anger et al., 2015).

Demerouti et al. (2001) introduced a job-demands and resources (JD-R) model for explaining the relationship between job characteristics and burnout using two dimensions of burnout scales (Figure 2.1). The two dimensions of exhaustion and disengagement are measured using the Oldenburg burnout inventory (OLBI) by Demerouti, Bakker, Nachreiner, and Schaufeli (2000). The exhaustion was defined by Demerouti et al. (2001) as a consequence of intensive physical, affective, and cognitive strain; they pointed out that MBI has the following limitation: one-sided scales can be inferior compared to the scales that include both positively and negatively worded survey items since this limitation will increase acquiescence tendencies. Thus, positively and negatively worded items are more likely to be clustered. To overcome this potential possibility, the OLBI scales include both positively and negatively worded survey questionnaires (Schaufeli & Bakker, 2004). That is, both exhaustion and disengagement are measured using sets of questionnaires that necessitate both affirmative and negative responses. Conversely, the OLBI covers both the affective aspect as well as the physical and cognitive aspects of exhaustion. Therefore, OLBI is more applicable to workers who conduct physical work such as construction labor, especially because the feeling of exhaustion consists of more than just emotions. Disengagement dimension in the OLBI was defined as distancing oneself from worker’s work and experiencing “negative attitudes toward the work object, work content, or one’s work in general” (Demerouti et al., 2000, pp. 455). Although the depersonalization scale in MBI includes cynical attitudes toward service or care recipients, the disengagement scale in OLBI is designed to measure attitudes toward the work task as well as the devaluation and mechanical execution of tasks. (Demerouti et al., 2001).

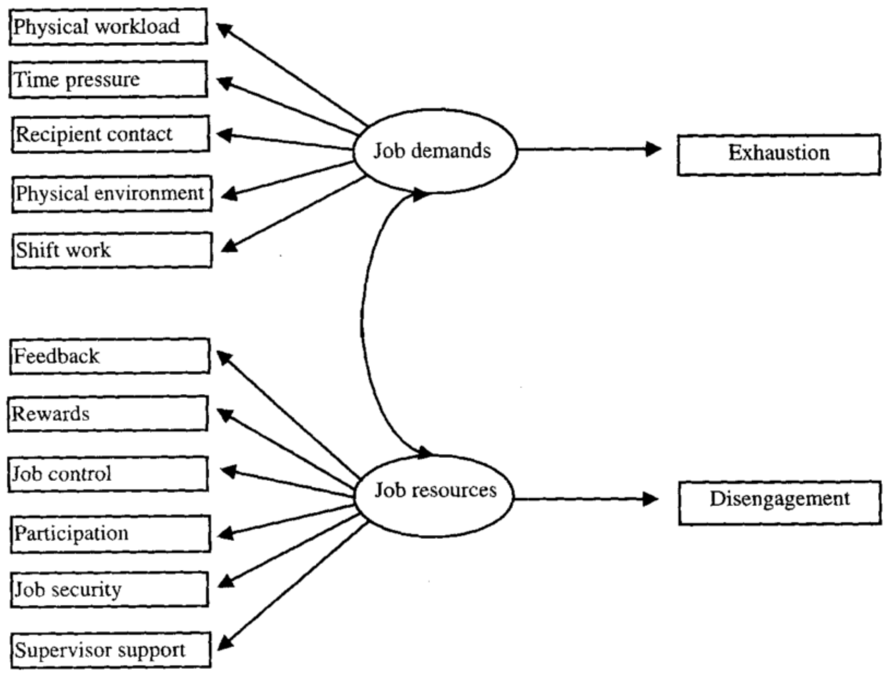

Figure 2.1 Job demands and resources (JD-R) model for burnout (Demerouti et al. 2001; pp. 502)

Bakker, Demerouti, and Verbeke (2004) expanded this model to explore how burnout affects a worker's performance. Bakker et al. expanded the job demands-resources model in order to study the relationship between job characteristics, burnout, and performance. Bakker et al. identified two types of performance, which are in-role and extra: (1) In-role performance includes meeting organizational objectives and effective functioning, such as a person's target productivity; (2) Extra-role performance is defined as organization citizenship behaviors such as the willingness to help colleagues and the avoidance of problems with colleagues. Job demands (e.g., work pressure and workload) were the crucial antecedents of exhaustion among the burnout dimensions in the findings of Bakker et al. The scope of this dissertation study is focused on the individual level of job characteristics which require more physical aspects of job demands and resources. Team-level performance was excluded from the general model introduced by Bakker et al. because the extra-role performance is often observed within the organizational and team context. Considering the scope of this dissertation research as an individual-level study, I only focus on in-role performance, which is the outcome required to meet the goals of the organization (Motowidlo & Van Scotter, 1994).

Nahrgang, Morgeson, and Hofmann (2011) evaluated the job demands-resources (JD-R) model of the relationship between job demands, resources, and burnout with workplace safety-related outcomes. The model presented in Nahrgang et al. was tested using a meta-analysis of occupations in the construction, healthcare, manufacturing, and transportation groups. The notable findings of Nahrgang et al. are that job risks and hazards have a positive relationship with burnout, which in turn has a negative relationship with safety performance. Li, Jiang, Yao, and Li (2013) investigate the effectiveness of the JD-R model to explain the variation of safety outcome based on the mediating effect of emotional exhaustion and safety compliance for crude oil production workers in China. Both Nahrgang et al. and Li et al. tested the JD-R model for safety outcomes, including accidents and injuries, adverse events, and unsafe behavior. These studies evaluated the performance outcome in only the safety dimension, but productivity is also related to job demands, resources, and burnout in the same manner; occupations that involve labor-intensive tasks, such as construction, should consider workers' job characteristics.

2.2 Research Questions

Few research models have been introduced and facilitated to understand the etiology between job demands and resources and performance of construction workers, and workers in other closely related occupations. Understanding the relationship between job demands and resources affecting construction workers' performance has remained a black box. To this end, construction workforce productivity, safety, health, and well-being studies have been compartmentalized. The individual-level research on workers' attitude and behavior has been under-investigated. The existing research has validated the JD-R, burnout, and performance models by relying on self-reported data and survey instruments. Among researchers on burnout, a need has been raised to test the model by measuring burnout constructs using different assessment methods such as the physiological assessment of health (Schaufeli, Maslach, & Marek, 1993) and this proposition is still rarely investigated by researchers. Thus, for the existing body of knowledge, it is crucial to combine isolated explanatory studies that investigate the causal relationship of issues identified from current industry records. The purpose of this dissertation study is to understand how task demands and personal resources affect construction workers' performance and whether a mediating mechanism could exist in the relationship between job characteristics and workers' performance. This study will validate a modified JD-R model at task level for construction workers. Ultimately, by testing the research model adapted from the JD-R model, this study is expected to find the interrelationship of fragmented safety and productivity improvement research by measuring worker performance in both safety and productivity dimensions.

Few studies have been conducted with the purpose of objectively measuring the effects of workers' good health, fitness, and well-being on their job performance in construction-industry occupations, which is an issue stemming from the use of self-reported data and survey instruments. Cordes and Dougherty (1993) pointed out that the way to improve the internal validity of job burnout research is to conduct experimental or quasi-experimental research. Productivity and safety are the parameters traditionally used to evaluate project performance. In general, labor productivity is a crucial outcome of effective human resource management used by an organization (Datta, Guthrie, & Wright, 2005).

An additional research question should be addressed in order to explore the method of applying wearable sensors for human-resource management research in the field of construction. In contrast to existing research, which tests the JD-R and burnout models to evaluate their effects on a single outcome parameter (i.e., productivity or safety), this dissertation study measures the unique characteristics of construction performance in two dimensions: productivity and safety. The key contributions of the study are increased understanding of construction workers' physical strain and psychological stress, and an assessment of the effects of physical strain and psychological stress on task and individual levels of performance. In summary, this dissertation research answers the following research questions, which were determined based on the job characteristics, unit of analysis, and scope of research:

> *Research Question 1*: How are task demands and personal resources associated with construction workers' performance?
>
> *Research Question 2*: What mediating mechanism exists in the relationship between task/personal characteristics and workers' performance?
>
> *Research Question 3*: Are the job demands-resources model and burnout theory still supported in the study of individual construction workers at the task level?
>
> *Research Question 4*: How can data collected from wearable technologies provide more meaningful insights for construction workforce management?

2.3 Research Objectives

First, the objective of this dissertation research is to understand the relationship between job characteristics and performance on both task and individual levels for construction workers. Second, this dissertation research is aimed at understanding the black box mechanism of burnout for construction workers in the aforementioned relationship. Ultimately, by testing the research model, this dissertation research investigates a means of tracking the interrelationship of fragmented safety and productivity improvement research. Additionally, this research introduces a new measurement method using wearable sensors to indicate research constructs, and revisits the JD-R model to validate the method through objectively measured sensor data. This dissertation study is significant because it seeks to examine existing research models by using an interdisciplinary approach to integrate fragmented studies. Furthermore, this study is also needed to determine the direction for further understanding of wearable physiological status and activity monitoring sensors which are intended to help mitigate productivity, safety, and workforce issues in construction. Additionally, this dissertation examines and applies existing research models of the combined job demands-resources and burnout models, using an integrated and interdisciplinary approach. Lastly, this research provides methodological guidelines to measure construct factors in research models through wearable sensor technologies.

This dissertation study measures workers' performance in ergonomics safety along with the concept of TWH. According to an article presenting an overview of the concept of burnout by Schaufeli, Leiter, and Maslach (2009), the existing definition of burnout was originally intended for human services occupations:

> "Burnout is a psychological syndrome of emotional exhaustion, depersonalization, and reduced personal accomplishment that can occur among individuals who work with other people in some capacity." (Maslach et al., 1997, pp.192); "…a state of exhaustion in which one is cynical about the value of one's occupation and doubtful of one's capacity to perform." (Maslach et al., 1997, pp.209); "…a depletion of physical resources supporting combustion to the psychological domain." (Schaufeli et al., 2009, pp.206).

While most of the literature discussed above has focused on the symptoms of chronic burnout, this dissertation research investigates whether symptoms of acute burnout can be measured using wearable sensors that provide feedback to construction workers to help them mitigate symptoms that could adversely affect their performance. The following studies discuss the symptoms of burnout which can occur in the short term (i.e., acute burnout or daily burnout experiences). Koutedakis (2000) introduced a type of acute burnout which occurs as a consequence of an imbalance between exercise and recovery overtime in just a few days or a week, and can disappear shortly if the burnout's cause is removed. Sonnentag (2005) discussed a type of acute burnout that can occur due to day-specific stressors or lack of resources, and highlighted how workers cope with their perceived day-level acute burnout. Frew and Sellaro (1994) classified the stages of burnout symptoms into acute and chronic categories to predict the retention or dropout rates of trainees among managers at General Electric company jobsites. Acute burnout can be distinguished based on the phase of burnout symptoms (Golembiewski & Munzenrider, 1988). If acute burnout can be detected in advance, the consequences of the symptoms can also be proactively prevented. The application of wearable sensors in burnout research could be beneficial because it allows for continuous sampling to collect physiological parameters, sleep quality, and activity levels that capture workers' daily exposure to burnout; this new approach is in accordance with Xanthopoulou and Meier's (2014) statement regarding the need for a new type of data collection protocol for daily burnout research. Thus, this dissertation proposes a different approach to operationalize the research construct in the current JD-R model to validate the concept of TWH. This dissertation research aims to control and minimize the effects of burnout through proactive management of potentially unsafe behavior and impaired productivity.

Chapter 3 Research Methodology

Adopting the job demands-resources (JD-R) model, this chapter proposes a revised model to fit with the current research objectives and unit of analysis. Section 3.1 presents a set of hypotheses to investigate the interrelationships between JD-R, burnout, and performance for the individual construction worker at the task level, based on findings of prior research, and propositions of the preparatory work. Section 3.2 presents proposed models and potential revised models based on the developed hypotheses. Section 3.3 introduces the operationalization of research constructs in the models. Section 3.4 summarizes the instruments that correct the data to measure the research constructs in the model. Section 3.5 introduces the experimental design and procedures.

3.1 Research Hypotheses

3.1.1 Task Demands and Exhaustion

Bakker et al. (2004) found that job demands are an important antecedent of the exhaustion dimension of burnout, based on research conducted with various job occupations and positions, including construction and industrial work. Li et al. (2013) also found a positive association between job demands and emotional exhaustion among crude oil production workers. The Encyclopedia and Dictionary of Medicine, Nursing, and Allied Health defines fatigue as “a generalized feeling of tiredness or exhaustion” (Miller & Keane, 1997, pp.585); thus, exhaustion and fatigue could constitute the same context for conceptualizing burnout. Several researchers (e.g., Holden et al., 2011) introduced the task-level approach of the JD-R model evaluation (as opposed to job-level), and Consiglio, Borgogni, Alessandri, and Schaufeli (2013) tested the JD-R model, differentiating between individual level and team level. The demand was used to measure workload (e.g., Hart, 2006), or workload was used to operationalize demand (e.g., Demerouti et al., 2001). The terms “workload” and “demand” were used interchangeably in occupational fatigue research (Fan & Smith, 2017). It is known that there is a positive relationship between the intensity of task demands and level of exhaustion. MacDonald (2003) categorized the task demand factors that influence workload as physical, sensory, central processing, psychomotor, and affective factors. In considering the task characteristics of construction jobs and the unit of analysis in this study (i.e., the task- and individual- levels), the current research uses the physical aspects of task demands as the predictor of physiological and psychological exhaustion. MacDonald found that the workload is a key contributor to stress and fatigue among workers involved in repetitive manufacturing tasks. Ergonomically and physically strenuous work is one of the key predictors of higher fatigue among the employed members of the Swedish population aged between 16 and 84 years old (Å kerstedt, Fredlund, Gillberg, & Jansson, 2002). Thus, the physical task demands relate to physical and mental exhaustion. Therefore, the current research hypothesizes that

> *Hypothesis 1 (H1)*: Higher levels of task demands are associated with higher levels of exhaustion.

3.1.2 Personal Resources and Exhaustion

Among the individual level of personal resources needed to complete physically demanding construction tasks, personal resources need to be further categorized into physical factors, such as fitness (especially relating to tasks), health status, and wellness. Kenny, Yardley, Martineau, and Jay (2008) described cardiovascular, respiratory, metabolic, and muscular functions as the components of functional work ability that affect physically demanding work. In particular, cardiorespiratory fitness and musculoskeletal capacity decrease in the aging workers group, which eventually causes work-related fatigue (Kenny et al., 2008). Based on reviews on burnout research performed with human service professionals, Kahill (1988) found substantial evidence of a positive association between burnout and poor physical health. Gorter, Eijkman, and Hoogstraten (2000) found that poor health status, such as experiencing physical inconvenience related to the level of burnout among Dutch dentists. Following the concept of Total Worker Health® (TWH) introduced by the National Institute for Occupational Health and Safety (NIOSH), the physical factors beyond the workplace that should be considered include sleep quality, off-duty levels of physical activity, and so forth (Lee, 2017a). Thus, a higher level of personal resources is associated with a lower level of exhaustion. Therefore, this current study hypothesizes as follows:

> *Hypothesis 2 (H2)*: Workers who have higher levels of personal resources are less likely to be exhausted.

Bakker et al. (2004) state that their results showed no significant interaction effect of organizational level of job resources (measured by autonomy, possibilities for self-growth, and social support) on the relationship between job demands and exhaustion. Xanthopoulou, Bakker, Demerouti, and Schaufeli (2007) hypothesized that the effect of job demands on exhaustion would be lower if the personal resources (measured by optimism, self-efficacy, and self-esteem) are high. Xanthopoulou et al. (2007) rejected this hypothesis of the buffering effect of personal resources on the relationship between job demands and exhaustion. However, different types (i.e., physical capability and fitness) and level (i.e., task level) of job resources were measured in this current dissertation study, in contrast to prior research (e.g., Bakker et al., 2004), which measured autonomy and social support as the indicators of job resources. The fitness for duty, including individual physical condition is the essential physical capacity for physically demanding occupations, such as firefighters and soldiers (Serra et al., 2007). Thus, testing the buffer effect of personal resources on the relationship between task demands and exhaustion is still valuable for this study as a means of explanatory research. This study tests an additional hypothesis (*Hypothesis 2**), which modified *Hypothesis 2* to test the buffering effect of personal resources on the relationship between task demands and exhaustion as follows:

> *Hypothesis 2* (H2*)*: Personal resources buffer the extent of influence of task demands on the increase in exhaustion.

3.1.3 Personal Resources and Disengagement

Xanthopoulou et al. (2007) expanded the job demand and resources model by adding a personal resources dimension. They measured personal resources using three manifest variables (organizational-based self-esteem, self-efficacy, and optimism), which focus on the psychological and social aspects of individual characteristics. Xanthopoulou et al. tested reciprocal models, examining the relationships between job resources, personal resources, and work engagement. Hätinen, Kinnunen, Pekkonen, and Aro, (2004) conducted personal perspective burnout research and found task-oriented coping and sense of coherence to be important personal resources associated with the lower level of burnout among clients from a rehabilitation center in Finland. Garrosa, Moreno-Jiménez, Rodríguez-Muñoz, and Rodríguez-Carvajal (2011) investigated the relationships between personal resources, engagement, and burnout in a cross-sectional study of 508 nurses and found that role stress was the predictor of burnout and engagement, while controlling for socio-demographic information and personal resources. Sonnentag (2017) found that from a task-level perspective, work engagement also includes the subset of constructs for task engagement. This current research proposes measuring personal resources as physical capabilities, while considering construction tasks and job characteristics at the task and individual level. Physical capability has been measured by several researchers, such as Åstrand (1960), who introduced a method of predicting aerobic work capacity using cycling, step, and treadmill (i.e., walk or running) tests. As the unit of analysis in this current study is at the task and individual level, the construct of engagement is more specifically scoped down to task engagement over work engagement. It is expected that physical capability for performing work be positively related to task engagement. In accordance with the Oldenburg Burnout Inventory, disengagement (which is the reverse concept of engagement) is included in the hypothesis testing and research model. Thus, the current research hypothesizes that

> *Hypothesis 3 (H3)*: Workers who have higher personal resources are less likely to be involved in task disengagement.

3.1.4 Exhaustion and Disengagement

The JD-R model (Bakker et al., 2004) demonstrated that exhaustion leads to disengagement, with a positive but weak relationship. However, a survey questionnaire study using the three most frequently used scales of burnout and engagement, validated that according to structural model analyses, all burnout and engagement scales represent negative relationships (Schaufeli, Salanova, González-Romá, & Bakker, 2002). Physical and mental fatigue leads to task disengagement among drivers (Matthews, 2002). Based on research conducted by Mathisen and Bergh (2016), a high level of exhaustion was associated with reduced engagement among oil production workers involved in offshore rig operations. Thus, this current study hypothesizes that the negative relationship between exhaustion and engagement is consistent at the task and individual levels among construction workers.

Hypothesis 4 (H4): Workers with a higher level of exhaustion are more likely to show increased task-level disengagement.

3.1.5 Exhaustion and Performance

The expanded JD-R model validates the negative relationship between exhaustion and in-role performance, while disengagement is more associated with extra-role performance (Bakker et al., 2004). As extra-role performance includes social interactions with team members, including citizenship behavior in the workplace, the research construct of extra-role performance was ruled out from the proposed model for the task and individual-level study. A research study conducted by Demerouti, Bakker, and Leiter (2014) demonstrated a negative association between employee exhaustion (measure by OLBI) and task performance evaluated by supervisors. The key performance indicators at the task and individual levels (i.e., micro view) in construction are productivity and safety (Lim & Mohamed, 1999). In the concrete pipe industry, safety is also used as one of the parameters to evaluate workforce performance (Shaw, Gupta, & Delery, 2002). According to some researchers (e.g., Cowing, Paté-Cornell, & Glynn, 2004), there is a tradeoff between safety and productivity. Moreover, some researchers (e.g., Mitropoulos & Cupido, 2009) have found that although challenging, it is possible to achieve both high safety and high productivity. Thus, the model needs to be tested by splitting performance into safety and productivity. Fatigue is a key risk factor associated with critical accidents in oil and gas construction fields (Chan, 2011). When working in a fatigued state, the safety performance of construction workers decreased and error rates increased (Fang et al., 2015). Fuller (2005) introduced a task-capability interface model to predict driver safety behavior, in which fatigue is one factor that decreases driver competence, which makes them lose control and cause accidents. Miller, Bates, Schneider, and Thomsen (2011) showed that increased fatigue from heat stress could cause impairments in mental function, which can lead to decreased worker safety. Many studies have explained the counter relationship between worker fatigue and productivity in various occupations (Folkard & Tucker, 2003; Jones, 1981; Karatepe & Uludag, 2008). This study hypothesizes the aforementioned relationship for physically demanding occupations at the task and individual levels as follows:

> *Hypothesis 5 (H5)*: Workers with a higher level of exhaustion are more likely to show decreased performance.

Additionally, the following hypotheses were separately tested by splitting the performance construct into safety and productivity performances.

> *Hypothesis 5*a (H5*a)*: Workers with a higher level of exhaustion are more likely to show decreased productivity performance.
>
> *Hypothesis 5*b (H5*b)*: Workers with a higher level of exhaustion are more likely to show decreased ergonomics-safety performance.

3.1.6 Disengagement and Performance

A study of 245 firefighters found that job engagement is a key antecedent of job performance at both the task and organizational levels (Rich, Lepine, & Crawford, 2010). Salanova, Agut, and Peiró (2005) presented a positive association between hotel employee engagement and performance at the organizational level. Kahn (1990) suggested that personal disengagement is a person's defense of preferred self with a lack of connection, passive behavior, and physical, cognitive, and emotional absence. Personal disengagement encourages incomplete role performance (Kahn, 1990). In a unit-level of meta-analysis research, Harter, Schmidt, and Hayes (2002) found that employee engagement was positively correlated with productivity measured by monthly revenue, which is a business-unit outcome. Based on research with Dutch teachers, Bakker and Bal (2010) showed that weekly engagement was positively associated with job performance. According to Hakanen and Koivumäki (2014), the increased level of work engagement among Finnish dentists was associated with higher level of clinical productivity, measured by the total paid procedure fees. The disengaged workforce was attributed to lost productivity, which is the "engagement gap" (Kowalski, 2003). Nahrgang et al. (2011) validated the prediction model of job demands and resources affecting burnout, engagement, and safety (e.g., accidents and injuries, events and unsafe behavior). Hansez and Chmiel (2010) found that higher work engagement was correlated with low situational (organization-related) and reduced routine (effort-related) violations among workers in the energy sector. Therefore, this study investigates the relationship between engagement and performance by hypothesizing as follows:

> *Hypothesis 6 (H6)*: Workers who have a higher level of task disengagement are more likely to show decreased performance.

The following two hypotheses were additionally tested by splitting the performance construct to investigate the relationship between not only engagement and productivity, but also safety outcomes.

*Hypothesis 6*a (H6*a)*: Workers with a higher level of task disengagement are more likely to show decreased productivity performance.

*Hypothesis 6*b (H6*b)*: Workers with a higher level of task disengagement are more likely to show decreased ergonomics-safety performance.

3.2 Research Model

Based on the research hypotheses established, Figures 3.1 to 3.4 present the research models that predict the performance of construction workers based on their task demands and personal resources with the mediating effects of exhaustion and disengagement. Figure 3.1, the simplest model among the proposed research models, is designed using a single performance construct measured by both productivity and safety indicators.

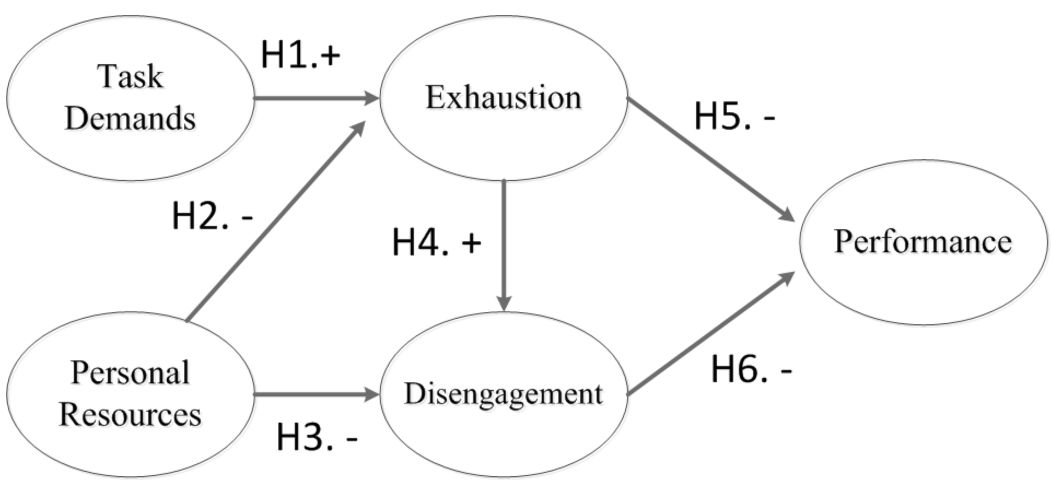

Figure 3.1 Proposed research model 1- with single performance construct

Figure 3.2 is a revised version of the research model in Figure 1, which tests the mediating effect of personal resources in the relationship between task demands and exhaustion.

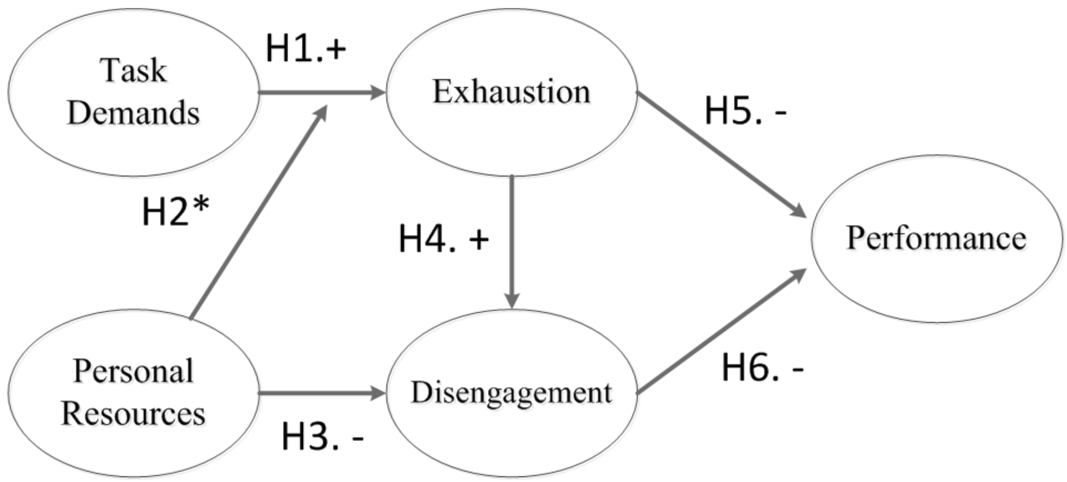

Figure 3.2 Proposed research model 2- testing the buffer effect of personal resources

Figure 3.3 and Figure 3.4 are revised versions of the research models in Figure 3.1 and Figure 3.2, respectively, which are designed using productivity and safety as individual research constructs that expect their performances to behave in a contradictory manner. This current study validates the model with better predictive power for the endogenous constructs in the proposed model, or is the best fit with data collected from sensor and survey instruments.

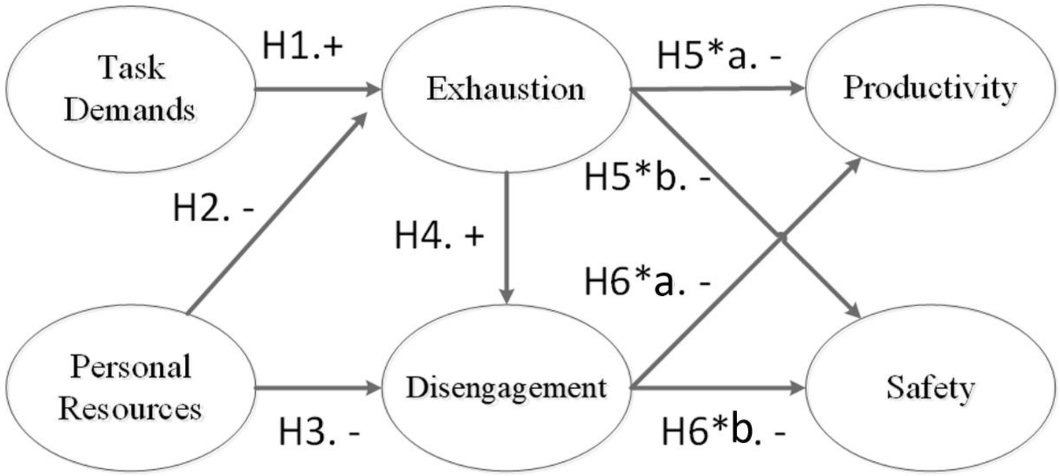

Figure 3.3 Proposed research model 3- with productivity and safety performance constructs

Figure 3.4 shows that personal resources do not directly associate with exhaustion, but rather buffer the relationship between task demands and exhaustion.

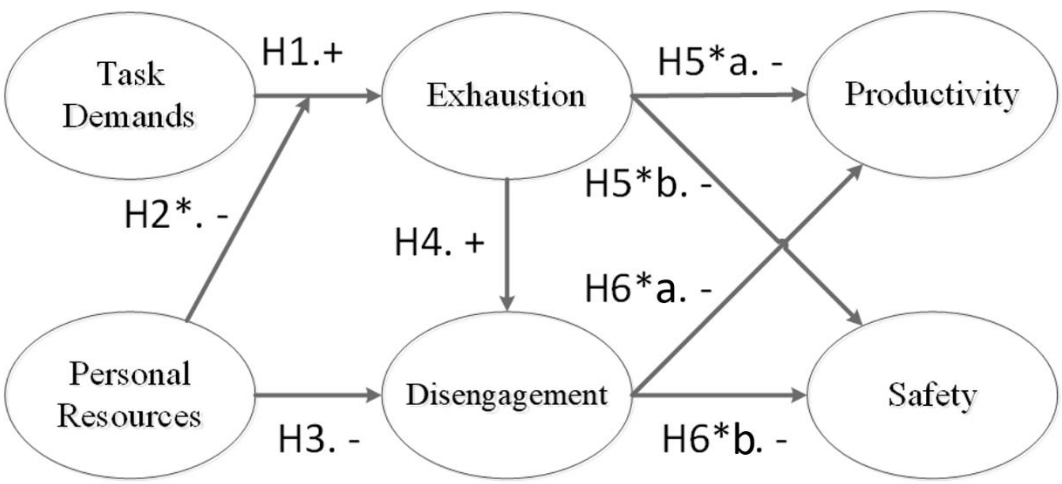

Figure 3.4 Proposed research model 4- testing the buffer effect of personal resources with productivity and safety performance constructs

Table 3.1 summarizes the hypotheses in the proposed models and the references that support these hypotheses. Based on the references listed in the table, the relationship between variables for each hypothesis is assumed to be linear. In total, 11 underlying hypotheses were derived and tested.

Hypothesis 5 and *Hypothesis 6* are developed to test the models in Figure 1 and 2, which include the performance as a single exogenous construct, measured by safety and productivity indicators. *Hypothesis 5*a* and *Hypothesis 5*b* were developed to separately test the association between exhaustion and productivity, and the association between exhaustion and safety, considering safety and productivity as a single construct in Figure 3.3 and Figure 3.4. Similarly, *Hypothesis 6*a* and *Hypothesis 6*b* also test the significance of the association between disengagement and safety, and the association between disengagement and productivity separately, in Figure 3.3 and Figure 3.4.

Table 3.1 List of hypotheses

#	Entities	Hypothesis	References
Hypothesis 1	Task demands-Exhaustion	Higher levels of task demands are associated with higher levels of exhaustion.	Å kerstedt, et al. (2002); Bakker et al. (2004); Li et al. (2013); MacDonald (2003)
Hypothesis 2	Personal resources-Exhaustion	Workers who have a higher level of personal resources are less likely to be exhausted.	Gorter et al. (2000); Kahill (1988); Kenny et al. (2008)
Hypothesis 2*	Task demands-Personal resources (moderation)-Exhaustion	Personal resources buffer the extent of influence of task demands on the increase in exhaustion.	Bakker, et al. (2005); Xanthopoulou et al. (2007)
Hypothesis 3	Personal resources-Disengagement	Workers who have higher personal resources are less likely to be involved in task disengagement.	Å strand (1960); Garrosa et al. (2011); Hätinen et al. (2004); Sonnentag (2017); Xanthopoulou et al. (2007)
Hypothesis 4	Exhaustion-Disengagement	Workers with a higher level of exhaustion are more likely to show increased task-level disengagement.	Bakker et al. (2004); Matthews (2002); Mathisen & Bergh (2016); Schaufeli, et al. (2002)
Hypothesis 5	Exhaustion-Performance	Workers with a higher level of exhaustion are more likely to show decreased performance.	Bakker et al. (2004); Demerouti et al. (2014)
Hypothesis 5*a	Exhaustion-Productivity	Workers with a higher level of exhaustion are more likely to show decreased productivity performance.	Folkard & Tucker (2003); Jones (1981); Lim & Mohamed (1999); Karatepe & Uludag (2008)
Hypothesis 5*b	Exhaustion-Safety	Workers with a higher level of exhaustion are more likely to show decreased ergonomics-safety performance.	Chan (2011); Fang, et al. (2015); Fuller (2005); Lim & Mohamed (1999); Miller et al. (2011); Shaw et al. (2002)
Hypothesis 6	Disengagement-performance	Workers who have a higher level of task disengagement are more likely to show decreased performance.	Bakker et al. (2004); Kahn (1990); Rich, et al. (2010); Salanova, et al. (2005)
Hypothesis 6*a	Disengagement-Productivity	Workers with a higher level of task disengagement are more likely to show decreased productivity performance.	Hakanen & Koivumäki (2014); Harter et al. (2002); Kowalski (2003)
Hypothesis 6*b	Disengagement-Safety	Workers with a higher level of task disengagement are more likely to show decreased ergonomics-safety performance.	Hansez and Chmiel (2010); Nahrgang, et al. (2011)

3.3 Operationalization

There are four selection criteria for the measurement of each research construct. First, this study uses at least one sensor (i.e., objective) and one survey (i.e., subjective) measurement for the reliability of measured indicators. Second, the instruments measuring the indicators should fit well with the proposed unit of analysis, research subjects, and the experiment. For instance, the questionnaire is appropriate for a subject not employed in construction but involved in assigned construction task (e.g., "I feel happy when I am working intensely"). Third, the selected data analysis method is structural equation modeling (SEM), as used by the job demands-resources model research. A linear relationship is assumed between construct and indicator. The relationship between a set of observed and unobserved variables is linear (Shah & Goldstein, 2006). Finally, the research model substantially reflects the concept of Total Worker Health® (TWH), as the new trend of occupational safety and health research; the subject's health status also needs to be quantitatively or qualitatively measured. The number of indicator variables per construct is ideally at least three, but four or more is excessive (Iacobucci, 2010). All of these should be continuous interval variables, not categorical variables.

3.3.1 Defining and Measuring Task Demands

Task demand also means workload, and the workload is the subset of job demand in this study. Physical workload was used as the indicator to measure job demands construct in the JD-R model (Demerouti et al., 2001). Å strand et al. (2003) introduce heart rate as the objective measurement of workload. By measuring heart rate, Abdelhamid and Everett (1999) assessed the physical demands of task activities in the concrete slab-laying and fishing trades. Abdelhamid and Everett

(2002) expanded the former study to measure physical workload in many other construction trades and activities such as brick laying, drywall installation, and ironwork using mean and peak heart rate. Heart rate is measured to estimate an acceptable workload in physically demanding occupations (Brouha, 1967; Saha, Datta, Banerjee, & Narayane, 1979; Wu & Wang, 2002). Heart rate was used as a critical indicator to predict the workload demand of police officers who performed mountain bike patrols (Takken, Ribbink, Heneweer, Moolenaar, & Wittink, 2009). Because heart rate is also inherently associated with age and resting heart rate, relative heart rate is the appropriate indicator for predicting the task demands that substantially reflect the subject's age and resting heart rate. The **relative heart rate** is positively associated with job demands, and therefore, it is the indicator of job demands at the individual level. Relative heart rate (RHR) is calculated based on following equation (3.1) defined by researchers in work physiology, ergonomics, and sports sciences (Kirk & Sullman, 2001; Rodahl, 1989; Wu & Wang, 2002),

$$RHR\ (\%) = \frac{HR_{work} - HR_{rest}}{HR_{max} - HR_{rest}} \times 100\% \tag{3.1}$$

where HR_{work} is the average of raw heart rate measured during work period, HR_{rest} is the resting heart rate measured from the subject in a sitting position in a chair for 10 minutes. HR_{max} is the maximum heart rate estimated by the equation (3.2) introduced by Tanaka, Monahan, and Seals (2001).

$$HR_{max}(bpm) = 207 - 0.7 \times age \tag{3.2}$$

The measured heart rate is the parameter used to estimate relative energy expenditure, and consequently, measures the physical workload (Garet et al., 2005). Varghese, Saha, and Atreya

(1994) suggested that energy expenditure estimated from heart rate is a variable that can predict workload. In this study, instead of the heart rate, the tri-axial accelerometer is used to measure energy expenditure. **Energy expenditure** is measured by ActiGraph, using tri-axial vector magnitude cut points with data collected using sensors on the subject's waist and non-dominant wrist. ActiLife (version 6.13.1) software developed for the data collected from ActiGraph adapted the validated energy expenditure algorithms of Freedson, Melanson, and Sirard (1998) and Williams (1998). The current study used ActiLife to estimate energy expenditure. Details of selected algorithms are summarized in Chapter 4, Data Analysis. Energy expenditure is used to classify the prolonged physical workload. Occupations in the building, iron and steel and agricultural industries reported energy expenditure of up to 7.5 kcal/min if there is little support from machinery or prefabricated materials (Å strand et al., 2003).

In addition, a survey instrument measured the **perceived workload**. NASA-Task Load Index (TLX) has been extensively used as the survey instrument for workload and has been applied to various occupational scenarios, including aircraft operations, nuclear power plant control rooms, simulated combat, and so forth (Hart, 2006). Mehta and Agnew (2011) used the NASA-TLX with university students to measure physical and mental task demand of simulated tasks in a laboratory setting. The subscales of NASA-TLX are developed to assess mental, physical, temporal demands, performance, effort, and frustration. DiDomenico (2003) introduced a method to estimate the workload subscale score independently in terms of physical and mental workload. Researchers have applied NASA-TLX frequently in construction engineering and management. Mitropoulos and Memarian (2013) used NASA-TLX to assess the subjective level of task demand on masonry construction workers. Chen, Taylor, and Comu (2017) used NASA-TLX to measure the workload (mental and physical load) in construction activities such as nut and bolt fastening and ladder climbing, in a laboratory setting.

3.3.2 Defining and Measuring Personal Resources

The **fitness**, **health**, and **wellness** of a worker in a physically demanding task are selected as the measured indicators and the components of personal resources. In terms of fitness, personal resources are the physical capacity and capability to perform assigned task demands. Bennell, Dobson, and Hinman (2011) introduced several types of physical performance (i.e., physical capacity to perform an activity) techniques such as Self-Paced Walk Test (SPWT), Stair Climb Test (SCT), Six-minute walk test (6MWT), and Timed up & go (TUG). The 6MWT is selected to measure cardiovascular capacity to measure subjects' fitness as personal resource, due to ease of implementation in the laboratory.

Heart rate recovery varies among individuals and influences the acceptable workload (Brouha, 1967). It can be estimated from the data collected while performing the main experiments by measuring the resting heart rate immediately after the assigned task. Heart rate recovery (HRR) is estimated as the heart rate change (beats per minute) value 2 minutes after peak heart rate at the end of the task. Cole, Blackstone, Pashkow, Snader, and Lauer (2000) used HRR as a predictor of mortality risk using the two-minute protocol. Lipinski, Vetrovec, and Froelicher (2004) reported a correlation between HRR and coronary artery disease by measuring the heart rate of 2193 men 2 minutes after exercise treadmill testing (i.e., the two-minute protocol). Broha (1967) noted that individuals with better physical capacity recover more rapidly from peak to resting heart rate.

Therefore, the greater the difference in heart rate measurements after two minutes, the better the physical capacity.

The JD-R model measured perceived autonomy, competence, and relatedness level that comprise job resources. However, based on the unit of analysis and characteristics of the assigned task in this study, perceived health status was selected as the indicator to measure the level of physical capacity, which is ultimately associated with the level of exhaustion and engagement while performing physically demanding tasks. Pohjonen and Ranta (2001) found that perceived health status positively influences the work ability of workers performing physically demanding tasks. The SF-12 short health survey was conducted using the methods introduced by Farivar, Cunningham, and Hays (2007) to reduce the inconsistency between SF-36 and SF-12. The latest version of SF-12 (SF12v2) has been used to survey general public health or to study patients by measuring health status in relation to living conditions (Larson, 2002; Lim & Fisher, 1999). The SF12v2 instrument was also used in various types of occupational health and safety research that integrate the promotion of workplace health (Park et al., 2015; Punnett et al., 2009).

With regard to wellness, this study measured sleep quality as a physical capacity and its influence on burnout and performance in the workplace. Powell and Copping (2010) found that sleep quality, as a wellness factor beyond the workplace is associated with a construction worker's fatigue in the workplace. The ActiGraph was utilized as an objective measure of sleep quality, owing to its high reliability, as validated and tested by many sleep researchers (Blackwell et al., 2005; Kripke et al., 2010). The data analysis phase of this study needs to investigate several sleep scoring algorithms used in the ActiGraph data analysis software.

3.3.3 Defining and Measuring Exhaustion

The Century Dictionary and Encyclopedia defines tiredness as “fatigue to the point of exhaustion” and uses the term “fatigue” in association with overexertion. The Gale Encyclopedia of Medicine states, “Fatigue is physical and/or mental exhaustion that can be triggered by stress, medication, overwork, or mental and physical illness or disease.” (Gale Research Company, 2002, pp. 1295).

Thus, physical exertion and strain, as well as mental fatigue, contribute to the occurrence of exhaustion. This study also examined the literature on exhaustion defined as fatigue, tiredness, exertion, and strain. As the objective measurement of exhaustion, **heart rate variability (HRV)** was used as the indicator in occupational safety and health and sports science research. Earnest et al. (2004) found a negative association between HRV and physical exertion, as observed in professional cyclists in a road cycle competition. The measured HRV variable can be converted to an interval variable with ranges of detected signal frequency. For instance, a range of between 0.05 and 0.15 Hz can be recorded as 0.1 Hz HRV, as shown by Egelund (1982). Heart variability in this range, obtained using spectral analysis, is associated with driver fatigue. Nardolillo et al. (2017) used the HRV to quantify the onset of fatigue in an assembly line task in a manufacturing setting.

Exhaustion is a dimension of burnout in the JD-R model (Demerouti et al., 2001). The Oldenburg Burnout Inventory (OLBI) was used in the job-resources and burnout model (Demerouti & Bakker, 2008). The Borg category ratio (CR) 10 scale is the most frequently used survey instrument to measure the perceived level of exertion and fatigue in research on ergonomics and human factors. Turpin-Legendre and Meyer (2007) used the Borg CR10 scale to measure the perceived level of exertion in simulated physically demanding tasks. Hewlett, Dures, and Almeida (2011) introduced Checklist Individual Strength (CIS20R) as one of the effective instruments to measure subjective fatigue level. Beurskens et al. (2000) validated CIS20R as the instrument for measuring perceived fatigue among the worker population. This study uses the CIR because the engagement construct is a greater combination of physical and mental fatigue, and tracks the process of physical demands mixing with mental fatigue in the burnout mechanism. The subjective fatigue subscale consisted of eight questionnaires (CIS8R) from the CIS20R, which is commonly used and reported in fatigue research (Hewlett et al., 2011).

3.3.4 Defining and Measuring Disengagement

The ongoing trend in academic research is to use several burnout inventories, including the Maslach Burnout Inventory-General Survey (MBI-GS), Copenhagen Burnout Inventory (CBI), Oldenburg Burnout Inventory (OLBI) and the Utrecht Work Engagement Scale (UWES-9). Although this current study adopted the two dimensions of burnout in OLBI for hypothesis development, the questionnaires in the OLBI are not applicable to its research subjects (i.e., subjects were recruited from university students and a local apprentice training program owing to the limitation of accessing construction workplaces and workers). Therefore, the survey instruments are replaced by applicable questionnaires for the scope and unit of analysis in this study. May, Gilson, and Harter (2004) introduced an engagement scale consisting of three components: cognitive, emotional, and physical engagement. Only the physical engagement sub-scale from all survey questionnaires, as developed by May et al., is applicable in this current study, as the other sub-scales are more applicable to the work level of engagement than the task level. That is, psychological safety and availability, job enrichment, and supportive supervisor and coworkers are not within the scope of this study, which is designed for individual and task levels. However, the disengagement scale in May et al. was not validated in the burnout theory and the

JD-R model. Thus, this study eventually adopts the engagement scales from the Dundee Stress State Questionnaire (DSSQ) developed by Matthews, Joyner, Gilliland, Huggins, and Falconer (1999) and Matthews et al. (2002), and the Short Stress State Questionnaire (SSSQ) was validated for its agreement with burnout inventory scales for task engagement.

Electroencephalography (EEG) has been used as a method to objectively measure task engagement in the operational environment. Brain wave patterns can be detected and classified as Delta, Theta, Alpha, and Beta EEG frequency bands to objectively measure human cognitive engagement (Teplan, 2002). Berka et al. (2007) conducted a feasibility study on monitoring level of task engagement using EEG with subjects in military operations, by performing cognitive tests. Goldberg, Brawner, and Holden (2012) used Emotiv EPOC, which is an off-the-shelf and low-cost EEG brain-computer interface, during an army cadet cross-cultural interaction training exercise and showed that EEG can be used to measure the level of task engagement.

3.3.5 Defining and Measuring Performance

From a management perspective, the important indicators of successful performance in construction include units per man-hour (i.e., productivity) and safety (Cox et al., 2003). The practical method of measuring labor productivity is the unit rate productivity method, as this index is operable with an estimation of cost data of the construction project. Work sampling is one of the methods used to estimate task-level productivity and its reliability is validated (Liou & Borcherding, 1986). Cheng et al. (2013) used the work-sampling method to estimate task-level productivity of workers. While the work-sampling method is adaptable and easily measures productivity, this study used the inverted scale of the original index (i.e., man-hours per sq. ft.) for labor productivity measurement in sq. ft. per man-hour.

At project level, safety performance can be quantitatively measured by the OSHA recordable incidence rates and experience modification rating (EMR) (Jaselskis, Anderson, & Russell, 1996). According to Swedish symptom survey data, construction workers frequently reported experiencing work-related musculoskeletal disorders (WMSD) in the lower back, followed by the shoulder, and knee (Schneider, 2001). At the individual and task level, this study investigated safety performance by measuring ergonomic safety behavior during the assigned task. The characteristics of tasks in the majority of construction trades are repetitive and expose workers to the risk of musculoskeletal disorders (Spielholz, Davis, & Griffith, 2006). Levitt and Samelson (1993) posited that measuring worker behavior is a promising indicator that needs to be developed, while OHSA recordable injuries, incidence rate, and days lost to injury were traditionally used as indicators to measure safety performance. Khandan, Maghsoudipour, Vosoughi, and Kavousi (2013) suggest that the safety behavior of the workers engaged in lifting and carry tasks can be characterized as ergonomic behavior, and find that the ergonomic posture is the highly correlated with the unergonomic behavior of workers in a petrochemical company. The working posture can be quantified and classified as unsafe ergonomic behavior using an accelerometer sensor (Cheng et al., 2013; Lee et al., 2017b).

A summary of the indicators used to measure the research constructs in the proposed model is provided in Table 3.2. It describes which selected measurement variables explain the research construct. The selected instruments and measurements were not validated in the burnout theory and the JD-R model. Therefore, this study is more an exploratory study than a confirmatory one because the data analysis investigates which selected survey questionnaire and sensor measurements can be included as features to predict the endogenous constructs in the proposed research model.

Table 3.2 Research constructs and operationalization

Construct	Variable	Instrument	Unit	Reference (Selected)
Task Demands	Heart Rate	Zephyr BioHarness3 (Heart rate data)	Beat per Minutes	Abdelhamid & Everett (1999, 2002); Brouha (1967); Saha et al. (1979); Wu & Wang (2002)
	Relative Heart Rate	Zephyr BioHarness3 (Heart rate data)	%	Kirk & Sullman (2001); Rodahl (1989); Wu & Wang (2002)
	Energy Expenditure	ActiGraph Link (Non-dominant Wrist and Waist)	Kcal or MET	Freedson et al. (1998); Williams (1998)
	Perceived Workload	NASA-TLX	Numeric Score	Chen et al. (2017); Hart (2006); Mitropoulos & Memarian (2013)
Personal Resources	Fitness	6-Minute Walk Test	Numeric Score	Bennell et al. (2011)
	Heart Rate Recovery	Zephyr BioHarness3 (Heart rate data)	Numeric Score	Brouha (1967); Cole et al. (2000); Lipinski et al. (2004)
	Wellness: Sleep Quality	ActiGraph Link (Non-dominant Wrist)	Numeric Score	Blackwell et al. (2005); Kripke et al. (2010); Powell & Copping (2010)
	Perceived health status	SF12 Health Survey (SF12v2, acute)	Numeric Score	Farivar et al. (2007) Park et al. (2015); Punnett et al. (2009)
Exhaustion	Heart Rate Variability	Zephyr BioHarness3 (R-R interval data)	Various units	Earnest et al. (2004); Egelund (1982); Nardolillo et al. (2017)
	Subjective level of fatigue	The Checklist Individual Strength Questionnaire (CIS8R)	Numeric Score	Beurskens et al. (2000); Hewlett et al. (2011)
Disengagement	Perceived level of task disengagement	Short version of Dundee Stress State Questionnaire: Energetic arousal, Motivation, Concentration	Numeric Score	Matthews et al. (1999, 2002)
	Brain activities detected using Electroencephalography (EEG)	EMOTIV Epoc plus	14 channels signals	Berka et al. (2007); Goldberg et al. (2012); Teplan (2002)
Performance	Productivity	Video Recording	Unit (S.F.)/Manhours (hr)	Cheng et al. (2013); Liou & Borcherding (1985)
	Safety (Ergonomic safety behavior)	Zephyr BioHarness3 (Accelerometer data)	Neutral Posture/Non-neutral trunk flexion	Cheng et al. (2013); Khandan et al. (2013); Lee et al., 2017b

Figure 3.5 schematically shows which wearable sensors and instruments were intended to acquire the measurement variables of any research construct in an objective manner. Originally, the research proposed measuring each research construct using an objective measurement. However, the EEG could not be used owing to the limited budget of this study.

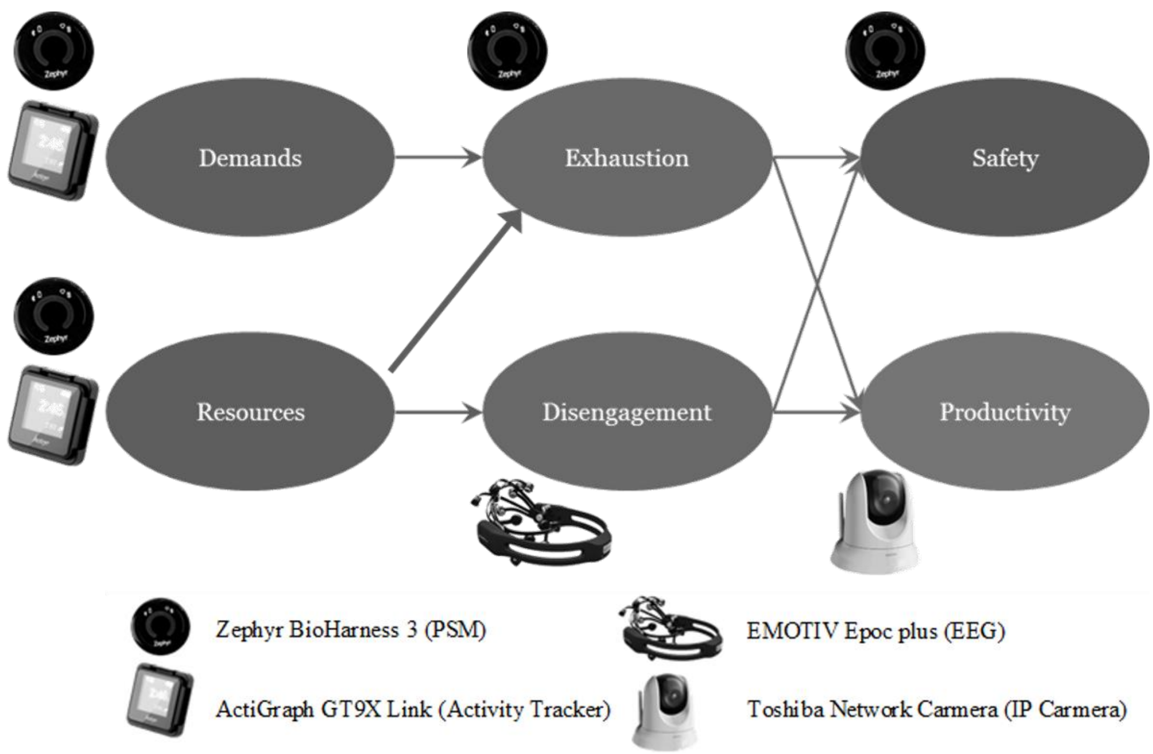

Figure 3.5 Wearable sensors and video monitoring application for the JD-R and burnout model

3.4 Instruments for Subject Recruitment

This section describes the survey instruments administrated to subjects in their recruitment phase to participate in the experiment.

3.4.1 Physical Activity Readiness Questionnaire

The Physical Activity Readiness Questionnaire *(*PAR-Q), developed by the British Columbia Ministry of Health and the Multidisciplinary Board of Exercise, was administrated to subjects during enrollment to see if they should be involved in the study experiments. The American College of Sports Medicine (ACSM) validates and provides the form. The original form was adapted and modified to screen for research subjects who face risks performing in a simulated concrete paver installation activity, which has a certain amount of physical demand. The Physical Activity Readiness Questionnaire (Par-Q) survey was administrated to screen out volunteers suffering from severe illnesses or those recently injured, with restrictions on physical activity.

3.4.2 Subject's Demographic Information

A demographic survey was conducted to obtain a subject's basic demographic information including age, weight, height, and dominant hand, which is needed to estimate physiological energy expenditure, and wearable sensors measured sleep-quality variables.

3.4.3 Medical History Questionnaire

The medical history questionnaire is adapted from the standardized form by Heyward (2002) to check the subject's hospitalization and medical history during the past 12 months and current perceived abnormal functioning of the body, physical pain, and so forth. Several questionnaires edited by Gatti (2012) were added, as the activity in the experiments requires cardiovascular, pulmonary, and musculoskeletal loads. This version of the questionnaire was adapted to screen out subjects who suffered from heart disease, asthma, or lower back pain.

3.5 Instruments for Experiment

This section describes the instruments adopted in the research experiments. The instruments were used to collect data, estimate variables, and operationalize the research constructs, as listed in Table 3.2. The experiment details are described in section 3.6.

3.5.1 Heart Rate Monitor

The selected heart rate monitor, Zephyr™ BioHarness3 heart rate monitor (Medtronic, Minneapolis, MN) is a non-invasive ambulatory wireless telemetry system that consists of Electrocardiography (ECG) electrodes attached via a chest belt. The product is comfortable, does not hinder the subject, and can be used for several hours. The battery life is long enough to collect data for an entire workday without interruption. The device can also log data without using local storage. This selected heart-rate monitor has been widely used in different scenarios, such as by first responders and construction workers (Buller, Tharion, Duhamel, & Yokota, 2015; Lee & Migliaccio, 2016; Smith, Haller, Dolezal, Cooper, & Fehling, 2014; Seo et al., 2016). The features of the Zephyr™ BioHarness3 heart rate monitor are summarized in Table 3.3.

Table 3.3 Features of Heart Rate Monitors (data from Zephyr Technology, 2012)

Property	Detail
Name	BioHarness^{TM}3 Performance System
Manufacturer	Medtronic
Dimension	28 (Diam) x 7 mm
Weight (without strap)	18 grams
Weight (with strap)	123 grams
Parameters Monitored	Heart rate, electrocardiography, breathing rate and depth, skin temperature (or core temperature), 3D acceleration, and body orientation
ECG sensor sampling frequency	1000 Hz
ECG amplitude range	0.25~15 mV
Heart rate rage	0~240 BPM
R-R	250~1500ms
Acceleration sampling frequency	100 Hz
Acceleration range (any axis)	-16~+16 g

Posture output from the Zephyr output range of -180° to 180° was used to classify the subject as either wearing the sensor lying down or standing up, and not for the purpose of trunk posture analysis. The raw three-axis acceleration data obtained from the accelerometer of a Zephyr sensor module worn under the armpit was used to estimate ergonomic risk factors using posture analysis software (the procedure is described in detail in Chapter 4, Data analysis). Lee et al. (2017b) showed that trunk posture analysis of the data obtained under the armpit is valid by comparing the placement of the Zephyr sensor and the gold standard method. The three-axis accelerometer data were measured in bit units between 0-4095, and this value was divided by 83 bits/g and converted into the g unit (i.e., 1g=83 bits) (Zephyr Technology, 2012).

3.5.2 Physical Activity and Sleep Monitor

The subjects wore the ActiGraph GT9X Link (ActiGraph LLC., Pensacola, FL) continuously on the wrist and waist while conducting simulated construction. The inertial measurement unit (IMU) in the ActiGraph Link combines the accelerometer, gyroscope, and magnetometer sensor data to record the subject's physical activity levels. The features of ActiGraph GT9X Link are summarized in Table 3.4. The subjects also wore the ActiGraph on their wrists during sleep to measure sleep quality. The subject's energy expenditure, metabolic equivalent of task (MET) rates, and sleep scoring were obtained using the manufacturer's data-analysis software, ActiLife 6.

Table 3.4 Features of Activity and Sleep Monitors (data from ActiGraph, 2016a)

Property	Detail
Name	ActiGraph GT9X Link
Manufacturer	ActiGraph, LLC
Dimension	3.5 × 2.5 × 1 (cm)
Weight	14 gram
Sample rate rage	30-100 Hz
Battery Life	14 days
Primary accelerometer dynamic range	-8g~ +8g
Secondary accelerometer dynamic range	-16g~+16g
Gyroscope dynamic range	-2000~+2000 degree/sec
Magnetometer dynamic range	-4800~+4800 micro-Tesla
Wear Location	Wrist, waist
Parameters Monitored	3D accelerometer, Gyroscope and Magnetometer, IMU unit temperature

3.5.3 Self-reported Health and Quality of Life (SF12v2)

The SF-12 survey is the short version of the SF36, focusing on the responder's subjective health status. It asks about the same eight health categories as in the SF36, and it can be answered in one to two minutes. Ware, Kosinski, and Keller (1996) used the short version of the SF-12 to successfully measure the subject's level of health and quality of life. This study used SF12v2, which is the latest version of SF-12. As the recall period of subjects is about one week, this study used the SF12v2 acute questionnaire to track weekly variability of the subjective health status of the subjects—the higher the score, the healthier the subjects.

3.5.4 NASA task load index (NASA-TLX)

The NASA task load index (NASA-TLX) is a multidimensional form used to measure subjective workload, consisting of six subscales of task load: physical, temporal, mental, effort, frustration, and performance level. The survey instruments were originally developed for and applied to aviation, but have been adapted beyond the original occupation for use with military automobile workers, power plant workers, drivers, medical professionals, and so on (Hart, 2006). As the subjects were required to complete several other survey questionnaires, Raw TLX (RTLX) was used, eliminating the weighting process of the six subscales to reduce the survey response time. Thus, NASA-TLX score was estimated without the weighting process.

3.5.5 Checklist Individual Strength Questionnaire (CIS)

Beurskens et al. (2000) designed 20 questions to measure work fatigue and to evaluate the validity of CIS20R in the working population. The CIS20R consists of eight items for subjective feelings of fatigue, five for concentration, four for motivation, and three for physical activity. For the purposes of this study, eight questions were extracted for the sub-score related to fatigue level as the interest of variables.

3.5.6 Short Stress State Questionnaire (SSSQ)

Matthews et al. (1999) developed the Dundee Stress State Questionnaire (DSSQ) to measure the stress status of respondents by measuring distress, engagement, and worry factors using 90 items. Helton (2004) developed the short version of the DSSQ by extracting 24 items and validating the short stress state questionnaire (SSSQ); eight items are correlated with the engagement factor. The responses to these eight items are converted to the level of disengagement to apply an explanatory variable in the proposed research model.

3.5.7 Video Recording

Four Toshiba IK-WB16A Internet protocol (IP) cameras recorded the subjects during the experiments. The video recordings were used to monitor the subjects' productivity and ergonomic safety behavior when lifting and lowering the construction materials.

3.5.8 Self-production Record Form

The subjects recorded their production progress each time one unit of the paver was completed. Every subject has a perception of the optimal production goal in the given task. The average goal of production was measured from a previous laboratory study conducted by Lee and Migliaccio (forthcoming) with the same type of simulated concrete paver installation work (i.e., average productivity measured by sqft/hour from 20 observations). The form also intends to allow subjects not to work on the simulated task by self-pacing. The subjects paced themselves based on the time spent (e.g., task start time and time remaining) compared to the initialized production goal on the self-production record form. Thus, the data collected from this form were not eventually used in the data analysis.

3.6 Experiment Procedure and Design

The subjects were recruited by word-of-mouth from junior and senior undergraduate classes and graduate-level classes of the construction management department at the University of Washington and by advertisements posted on the department's bulletin board. Additional subjects were recruited from trainees in a pre-apprenticeship construction education program. As the subjects had no previous experience as construction laborers, the target population was designed to be at the entry level of construction worker. Volunteers wishing to participate in the study signed a consent form, which was approved by the University of Washington Institutional Review Board (IRB). The subjects' contact information (email and mobile phone) was collected so that instructions on wearing the ActiGraph sensor correctly before sleep could be sent before the experiment participation date. Based on the subject's demographic information, ActiLife software was used to set up and initialize the ActiGraph for each subject. The subject received an ActiGraph set (i.e., sensor module and wrist strap) from a researcher on the day prior to each experiment. The subject had to wear the sensor on the day prior to the experiment for at least an hour before going to bed, to measure sleep efficiency.

In each session, the subject was required to wear heart rate (HR) monitors and ActiGraph sensors. The weak conductivity between the skin surface and the sensor caused signal noise in the heart rate data. The experiment procedures were planned so that each subject wore the HR monitor before the six-minute walk test. By moistening the subject's skin, the conductivity between skin surface and ECG electrodes was improved to reduce signal noise in the HR data. Throughout the experiment sessions, each subject wore two ActiGraph sensors: one on the waist and the other on the non-dominant wrist. The ActiGraph sensor on the wrist was worn using a wristband. A pouch connected to the belt loop was used to wear the sensor on the waist. The subject was instructed to wear the heart rate monitor on the chest.

The subject conducted the six-minute walk test and filled out the SF-12 survey. The six-minute walk test followed a standardized protocol in a 15-meter long (50 feet) corridor (Pepera et al., 2012). The track was laid out in a laboratory with an air conditioning system for consistency of indoor environmental conditions (Figure 3.6) and the subject's total walking distance was recorded. Each subject conducted the walk test in comfortable footwear but changed to steel-toe capped boots for the actual experiments. The SF-12v2 survey measured subjective levels of physical and mental health status. The acute version of the SF-12v2 survey questionnaire was used for the perceived health status of subjects per 1-week interval. Then, each subject wore personal protective equipment (PPE), had ergonomics training, and performed stretch and flex exercises for 20 minutes. After this procedure, the subject's resting heart rate was measured over 10 minutes while the subject was sitting in a chair.

Figure 3.6 Laboratory setup and layout for experiments

According to the Bureau of Labor Statistics data compiled by Wang et al. (2015), flooring work recorded the highest number of WMSD incidents among construction tasks. Flooring work requires highly repetitive movements (McGaha et al., 2014) and exposes workers to overexertion injuries (Schneider, 2001). Therefore, in this study, flooring work (i.e., installing pavers and pedestals of a raised deck) was experimentally designed with simulated construction activities. Each subject had to wear knee-protection pads, safety boots, and gloves. Safety glasses and hard hats were not provided, as there were no relevant hazards present during the simulated construction activities. The heart rate monitor recorded data on a sensor module, as well as transmitting live data to a radio signal receiver linked with the laptop. A researcher monitored the real-time heart rate level to prevent overexertion.

- *Session 1 (Task 1)*

  The subject was instructed to install 18-pound concrete pavers measured by12″(L)× 12″ (W) × 2″(H). The subject had to check the productivity report form every time they built one raised deck panel and note the optimal production goal obtained from the preliminary data collection phase. In a previous pilot study (Lee & Migliaccio, forthcoming), the average production time of a panel (36 inches by 72 inches) was 6 panels in 60 minutes.

- *Session 2 (Task 2)*

  The task procedure was the same as the task in Session 1. The difference is that the subjects installed two-pound paving pavers measured by 12″(L)× 12″(W)× 1.25″(H).

- *Session 3 (Task 3)*

  In Session 3, the subjects used the same size pavers as those in Session 1 (18 pounds, 12″(L)× 12″ (W) × 2″(H)) to assemble a 36-inch by 72-inch unit of concrete panels. The distinction between this task and Task 1 and Task 2 is that the height of the material handling area (i.e., wood palette) was adjusted based on subject's height, which is proportional to his/her knuckle height (i.e., reference location of controls for lifting). The height of the wood palette was between 28 and 35 inches, which is the range of knuckle height between the 5th percentile of women and the 95th percentile of men. Knuckle height is defined as the optimal height to exert lifting force (Pheasant & Haslegrave, 2016).

- *Session 4 (Task 4)*

  In Session 4, the subjects used the same size paving slabs as in session 2 (2 pounds, 12″(L)× 12″(W)× 1.25″(H)) to assemble a 36-inch by 72-inch unit of concrete panels. The distinction between this task and Task 1 and Task 2 is that the height of the material handling area (i.e., the wood palette) was adjusted based on subject height.

During the four task sessions, subjects were instructed to lift the pavers and to carry them with both hands. Table 3.5 summarized the four different levels of task demands according to the different weights of the pavers and the heights from which they were lifted.

Table 3.5 Four experimental task sessions

		Weight	
		High (18 lbs)	Low (2 lbs)
Vertical Height at the destination and origin of the lift	High (Lifting materials from the floor)	High-Workload (Session 1)	Medium-Workload (Session 2)
	Low (Lifting material from the adjusted working platform*)	Medium-Workload (Session 3)	Low-Workload (Session 4)

Note. The height of the working platform was adjusted between 26 inches (5th percentile of women's knuckle height) and 32 inches (95th percentile of men's knuckle height).

Once the installation of pavers was completed on the pedestals, subjects had to ensure that the horizontal and vertical alignment was acceptable (e.g., quality of work was consistent) and this was as their production output. If the subjects did not comply with these two instructions, they were redirected to correct the unqualified work during the experiment.

Figure 3.7 and Figure 3.8 describe the experiment settings, including the materials area, two installation areas, and the subject monitoring area. The figures also include the dimension of each area.

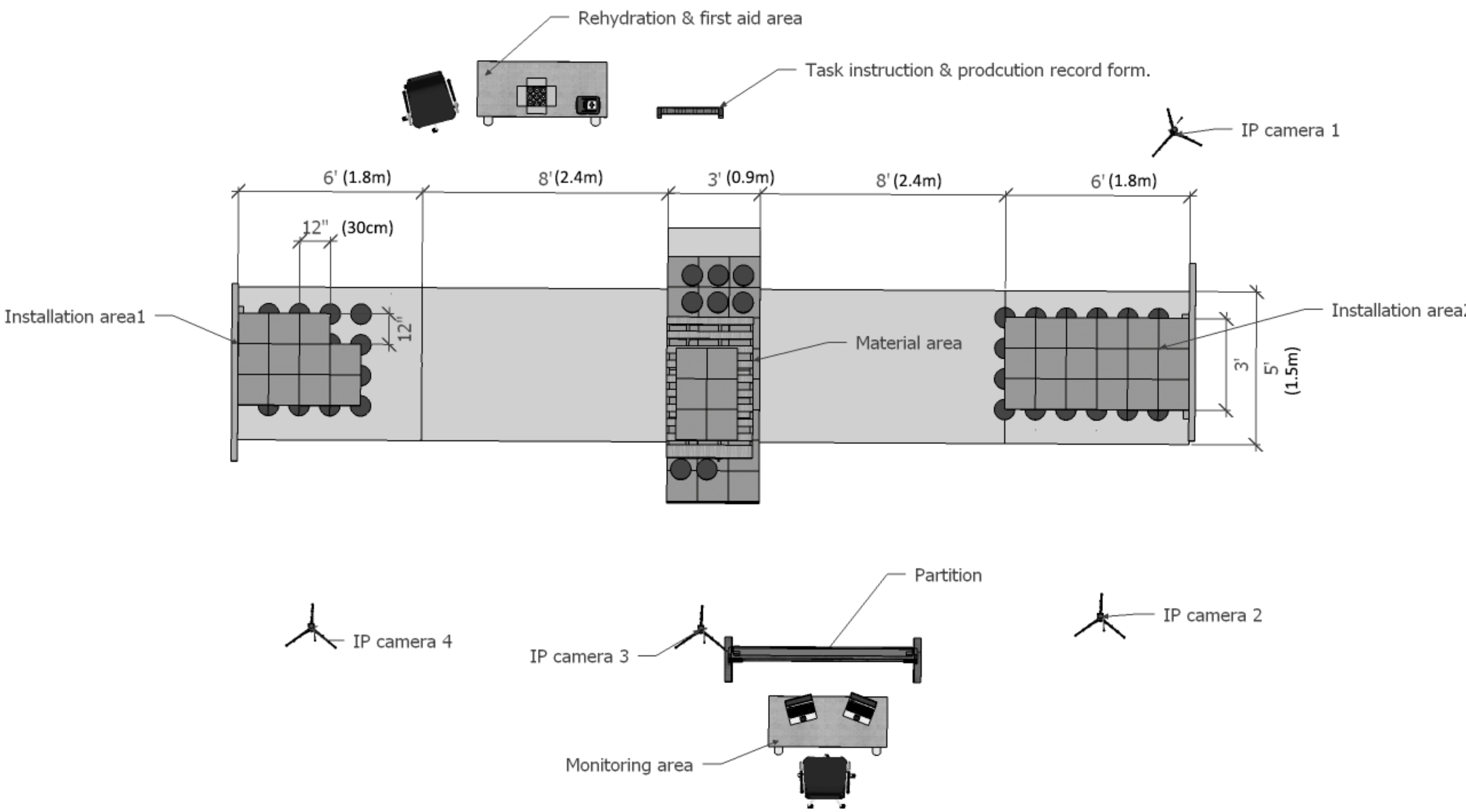

Figure 3.7 Dimension of working platform height (plan view)

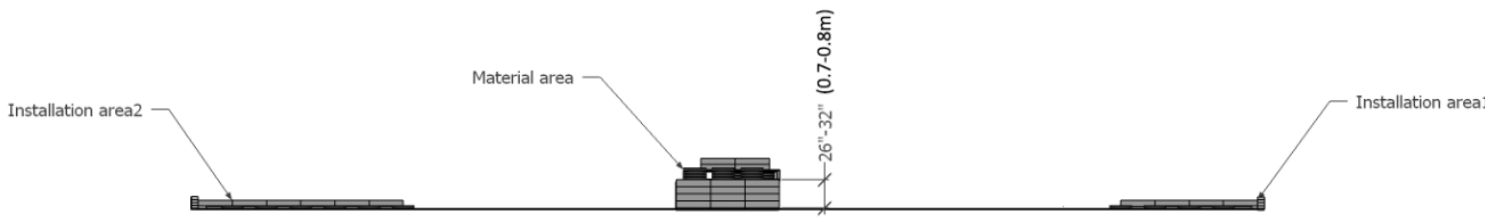

Figure 3.8 Dimension of working platform height (elevation view)

Owing to the limited number of pavers and pedestals needed to continuously conduct the task during the hour, a disassembler moved all the pavers and pedestals completed in installation area 1 back to the materials area (Figures 3.7 and 3.8). While a disassembler worked in area 1, the subjects assembled the floor in area 2. To minimize any social factors impacting subject behavior, the installer and disassembler worked on opposite sides of the working area but were able to share the materials inventory. Their verbal communications were minimal and restricted between the subject and disassembler.

One camera recorded the entire area of the simulated construction task to enable the researchers to count the number of paving and pedestals built in one hour. The other three cameras were placed with perpendicular views of the subjects in one materials area and two installation areas, as the video needed to be used for ergonomic posture analysis (Figure 3.9). Cameras were placed perpendicularly, 90° from the subject, to allow sagittal plane postures to be assessed, which is in accordance with the NIOSH observational-based posture assessment recommended guideline (Lowe, Weir, & Andrews, 2014). The guideline stated that the best orientation of the camera is to place the camera perpendicular to the plane of the subject's joint of interest (Lowe et al., 2014).

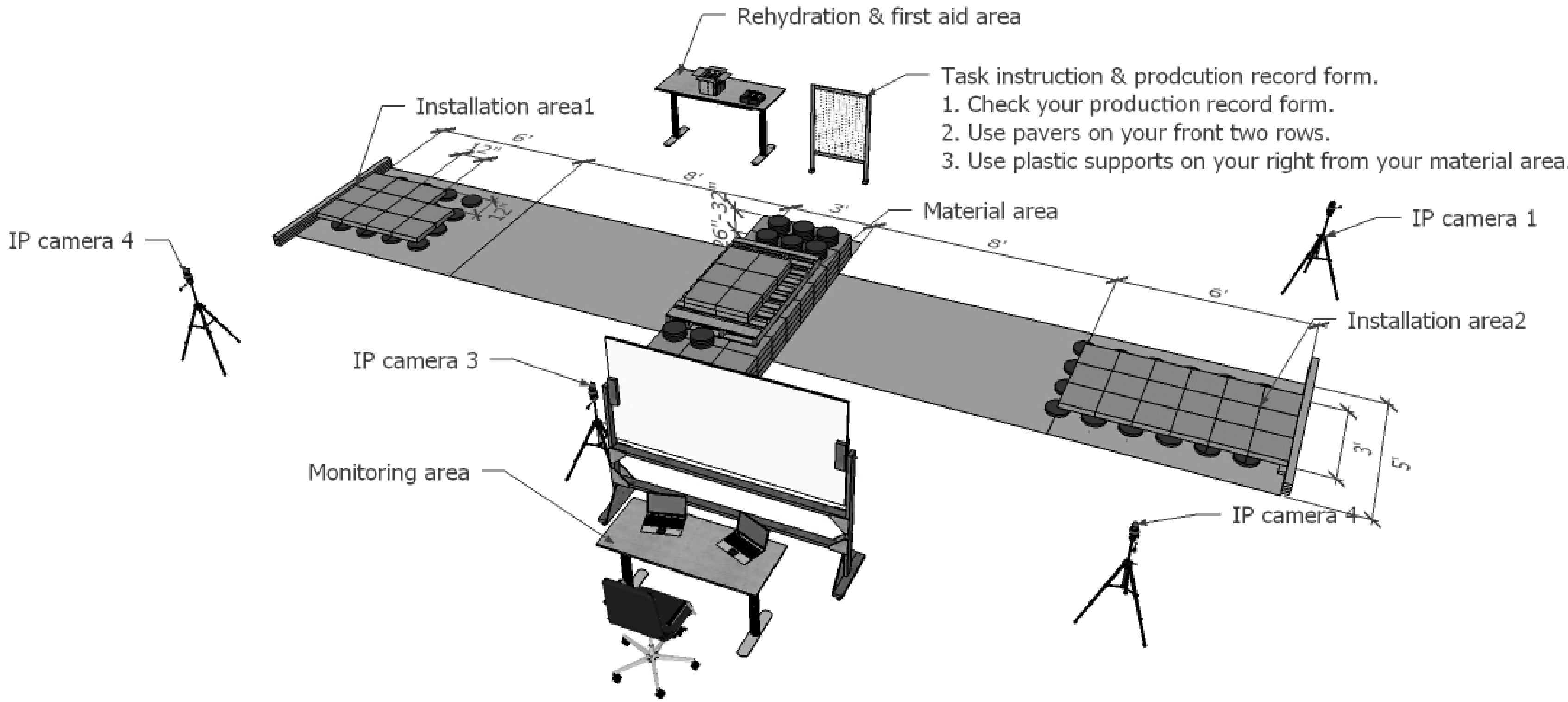

Figure 3.9 Experiment setting

After performing the simulated construction tasks for 60 minutes, subjects sat on a chair for 10 minutes and their resting heart rate was measured. Following the measurement of resting heart rate, subjects were given five minutes to fill out survey forms, including NASA-TLX, CIS, and SSSQ (Figure 3.10). The planned total time to complete the experiments was 120 minutes for each session. Each session was conducted at intervals of one week. One hand-held heat stress monitor was installed on the tripod and the wet-bulb globe temperature was logged on the universal serial bus-wired laptop. All collected data were stored as soon as each experiment session was completed. The data set was named and securely stored following the IRB protocol of the University of Washington before the data analysis was conducted.

Subjects were not allowed to have caffeine, take medication, or smoke for at least two hours before participating in the experiment. Subjects were only allowed water during the experiment. At the end of the experiment, subjects were given granola bars and water. The subjects were asked to participate in three additional experiment sessions. The recall period was greater than one week but less than two weeks.

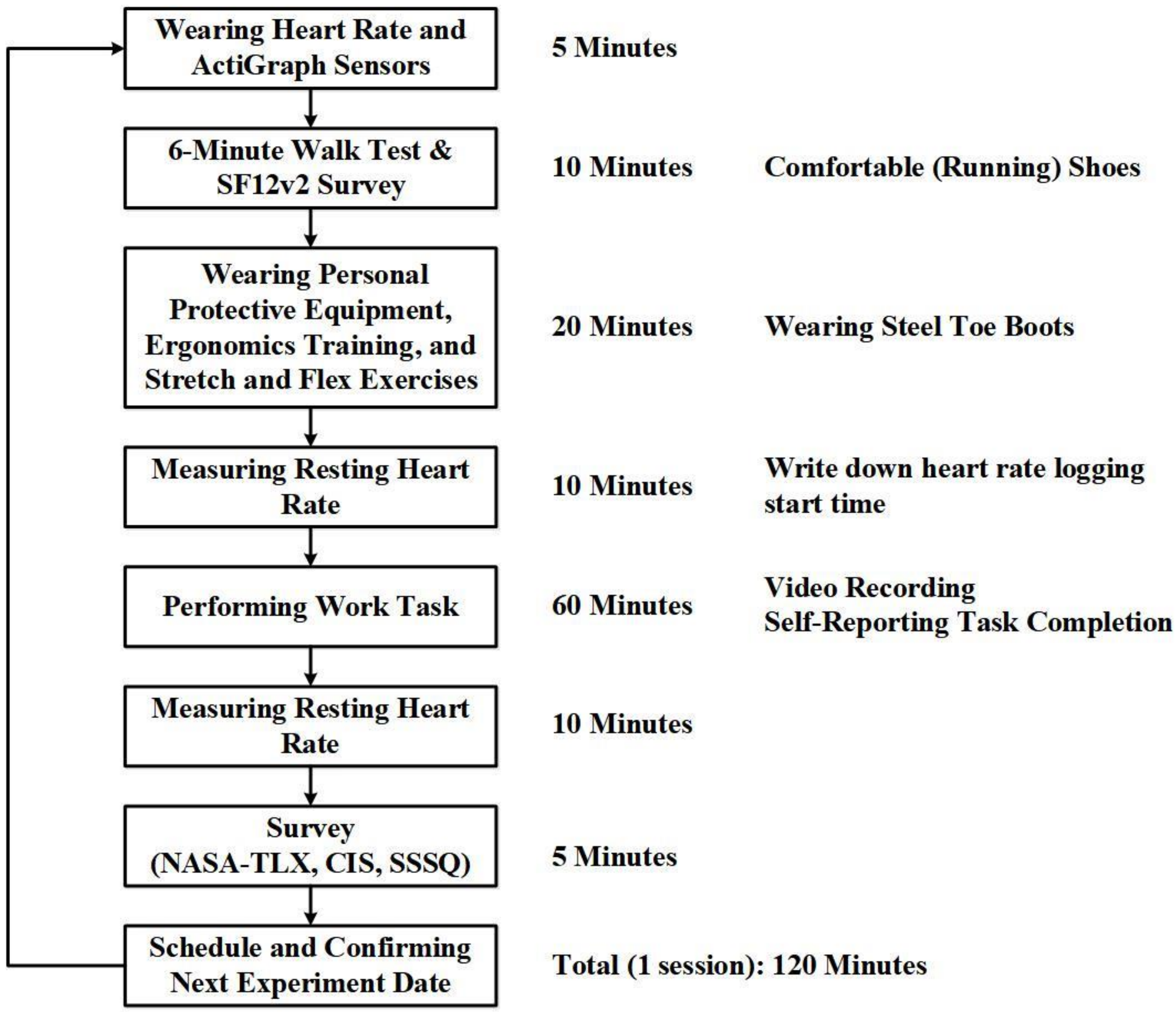

Figure 3.10 Experiment Procedure

Chapter 4 Data Analysis

This chapter describes the software utilized for data analysis, selection of structural equation modeling (SEM) methods, and procedures for model assessment and hypothesis testing. Section 4.1 introduces the software programs that were utilized for the analysis of data collected from the instruments introduced in Chapter 3 and summarizes the analytical processes for estimating research variables. Section 4.2 describes how the raw data were preprocessed to handle missing data and outliers. Section 4.3 introduces two SEM methods—covariance-based structural equation modeling (CB-SEM) and partial least-squares structural equation modeling (PLS-SEM)—to test the models and hypotheses introduced in this paper and describes the reason why PLS-SEM was chosen as the final data analysis method. Finally, the measurement model and structural model assessment methods for hypothesis testing are detailed.

4.1 Software

4.1.1 Zephyr™ performance systems software

A summary file containing the research subject's beat-to-beat RR interval, raw electrocardiogram (ECG) data, heart rate, breathing rate, and three-axis acceleration data can be downloaded utilizing the Zephyr™ BioHarness log downloader (V1.0.29.0) software (Medtronic, Minneapolis, MN). By utilizing the Zephyr™ Kubios R-R file format converter (Medtronic, Minneapolis, MN), the downloaded RR interval [i.e., normal-to-normal (NN) interval] file was converted into a file format for use in the heart rate variability (HRV) analysis software described in the following section.

4.1.2 Kubios HRV analysis software

The Kubios HRV analysis software (Kubios HRV Premium ver. 3.0.2., Kuopio, Finland) was utilized to analyze the time domain and frequency domain of the HRV measurements from the RR intervals of the raw ECG data collected from the heart rate monitor (Zephyr performance system). The Zephyr performance system collects the ECG data at 1,000 Hz, meaning it satisfies the necessary sampling frequency to accurately recognize an R-wave occurrence (the fiducial point on the ECG depicted in Figure 4.1), which ranges from 500 to 1,000 Hz (Berntson et al., 1997).

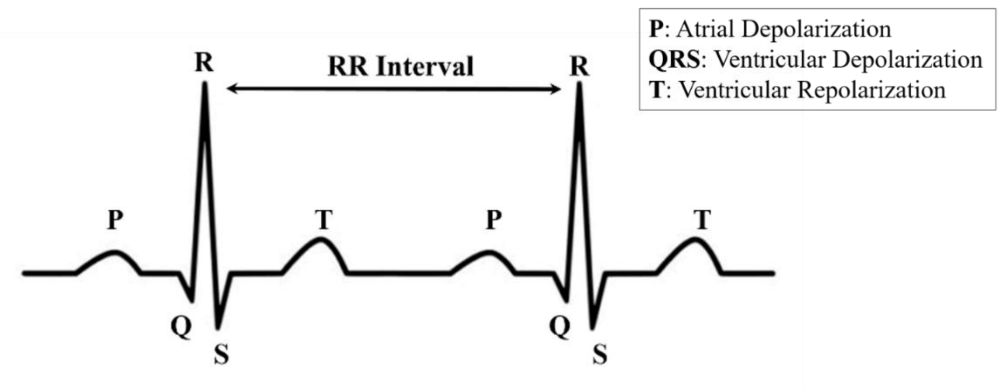

Figure 4.1 Sample electrocardiogram record

For HRV analysis, the time domain method and frequency domain method were selected in the Kubios HRV software. In time domain HRV analysis, two parameters, namely the standard deviation of all normal-to-normal intervals (SDNN) and root mean squared differences of successive NN intervals (RMSSD), which are popularly utilized for time domain HRV measurements in occupational health research (Togo & Takahashi, 2009), were estimated as indicators to measure a subject's level of exhaustion. The SDNN and RMSSD are considered to be the most important time domain measures (Medicore, n.d.). SDNN and RMSSD are estimated utilizing equations 4.1 and 4.2, respectively:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_j - \overline{RR})^2} \tag{4.1}$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N-1}(RR_{j+1} - RR_j)^2} \tag{4.2}$$

where N represents the total number of successive intervals, RR_j is the jth RR interval, RR_{j+1} is the RR interval following RR_j, and $\overline{RR}$ is the mean RR interval (Tarvainen, Niskanen, Lipponen, Ranta-Aho, & Karjalainen, 2017).

Lowered autonomic nervous system (ANS) activity is known to be the cause of decreased ability to cope with the continuously changing environments that evoke internal and external stressors (Medicore, n.d.). Reduced sympathetic nervous system (SNS) activity is related to loss of energy, fatigue, and insufficient sleep, and reduced parasympathetic nervous system (PNS) is related to the electrical stability of the heart in the presence of stress, anxiety, and panic (Medicore, n.d.). The imbalance between SNS and PNS is an indicator of stress-related health problems (Medicore, n.d.). For discrimination of the SNS and PNS contributions to HRV, frequency domain analysis was also conducted utilizing the Kubios HRV software because time domain analysis has limited ability to interpret SNS and PNS data separately (Acharya, Joseph, Kannathal, Lim, & Suri, 2006). Time domain analysis provides information useful for measuring the overall activity of the ANS and frequency domain analysis can estimate the degree of balance between the SNS and PNS. For the frequency domain parameters, the fast Fourier transformation (FFT) method was utilized for converting discrete time domain data into frequency domain data because of the simplicity of the algorithm and its high processing speed (Camm et al., 1996) for power spectral density (PSD) analysis. The FFT assumes that the sinusoidal signal is infinitely continuous. However, there were limited observation intervals for data collection of our experiments. Spectral leakage occurs when the sinusoidal cycle does not end at zero, meaning the FFT contains the spectrum from the adjacent components and glitches in the signal. The windowing method was utilized to reduce the amplitude of the discontinuities in the signal, which are a limitation of the FFT. The Kubios software was adapted from Welch's periodogram, which utilized windowing (Welch, 1967) to solve the spectral leakage problem in FFT domain methods (Tarvainen, Niskanen, Lipponen, Ranta-Aho, & Karjalainen, 2014). Spectral leakage was addressed by allowing overlap between the windowing and data segments prior to computing the periodogram, which is the spectrum of a set of time signals obtained from the FFT spectrum. In Welch's periodogram method, the window width was set to 300 seconds and window overlap was 50%, which corresponds to 150 seconds and creates three overlapping windows for a 10-minute (600 seconds) sample for analysis (Tarvainen et al., 2017).

In our FFT analysis, the HRV data were segmented into three power bands in the frequency domain: very low frequency (VLF: < 0.04 Hz), low frequency (LF: 0.04 Hz–0.15 Hz), and high frequency (HF: 0.15–0.40 Hz). LF is an indicator for assessing a subject's fatigue level based on the finding that there is a relationship between reduced LF HRV and fatigue levels (Dishman et al., 2000; Olsson, Roth, & Melin, 2010). HF was lower in elite athletes after training (with fatigue) according to RR intervals measured both in the supine and standing states (Schmitt et al., 2013). Normalized units for the LF and HF parameters were obtained based on 4.3 and 4.4, respectively (Tarvainen et al., 2014):

$$LF(nu) = \frac{LF(ms^2)}{TP(ms^2) - VLF(ms^2)} \times 100 \quad (4.3)$$

$$HF\ (nu) = \frac{HF(ms^2)}{TP(ms^2) - VLF(ms^2)} \times 100 \quad (4.4)$$

where the *TP* is the total power estimated variance of all *NN* intervals, which includes power ranges approximately less than or equal to 0.4 Hz, *VLF* represents the power in the VLF range (i.e., ≤0.04 Hz), and *nu* represents the normalized unit (Camm et al., 1996).

4.1.3 Posture Analysis Software

Posture analysis software developed by the University of Washington Ergonomics Laboratory based on LabVIEW (Rynell, 2010) was utilized to quantify a subject's ergonomic safety behavior. Raw three-axis acceleration data were acquired at 100 Hz utilizing a Zephyr sensor module worn under the left armpit of the subject. The posture analysis software utilizes two main processes. The first process removes noise from the raw data and downsamples the data to 10 Hz. In the second process, the downsampled data are processed to characterize trunk posture exposure. The trunk flexion/extension, lateral angles, and vector sum angles were calculated over one hour utilizing the resampled data. The LabVIEW code for the posture analysis software was modified to apply the rule of rapid upper limb assessment (RULA) tool developed by McAtamney and Corlett (1993) to calculate the percentage of total work time in each posture degree interval for trunk flexion/extension (i.e., degree < 20, $20 \leq$ degree < 60, degree ≥ 60).

Lee et al. (2017b) analyzed the agreement of trunk posture analysis results after placing ActiGraph and Zephyr sensors at seven locations on the upper body: under armpit, chest, head, shoulder, center-waist, side-waist, and back. Lee et al. (2017b) considered the ActiGraph chest placement as a gold-standard measurement and found that the Zephyr sensor worn under the armpit demonstrated acceptable agreement with the ActiGraph results in terms of trunk flexion posture (Table 4.1). Specifically, the ActiGraph sensor was placed on the sternum (chest) and the Zephyr sensor module was placed on the apex of the rib curvature (under armpit) in that study. Therefore, posture analysis for this study utilizing the Zephyr sensor under the armpit was considered to be as reliable as the gold-standard measurement tool and its placement (i.e., sternum).

Table 4.1 Comparison of posture analysis between ActiGraph and Zephyr sensors worn with different body placements (data from Lee et al., 2017b)

Posture category (% of time)	Trunk extension	Trunk neutral (Posture angle between -5° and 20°)	Trunk flexion (Posture angle between 20° and 60°)	Trunk flexion (Posture angle ≥ 60°)
ActiGraph sensor worn on Chest	0.0	60.8	23.9	15.3
Zephyr sensor on Chest	2.3	57.7	25.9	14.1
Zephyr sensor under Armpit	0.0	59.8	24.1	16.1

4.1.4 ActiLife Software

ActiLife version 6.13.1 (ActiGraph, LLC., Pensacola, FL), which is an ActiGraph data analysis software, was utilized to process the raw accelerometer data collected during our study. The ActiLife software supports different algorithm options and functions to optimize algorithms based on the placement of ActiGraph sensors worn on the body. The selection of algorithms and functions was also determined based on the biometric characteristics of subjects, including age, gender, height, and weight. This biometric information constituted the basic input data for each algorithm to calculate energy expenditure (EE) and metabolic equivalent of task (MET). The ActiGraph sensor setup was performed prior to the collection of data based on the inputs of biometric information, including gender, height, weight, date of birth, race, limb, side, and hand dominance via the ActiLife software. The limb input indicates which limb the ActiGraph sensor was placed on. Side represents the placement of the sensor from the subject's perspective (e.g., left or right) and dominance indicates whether the side where the subject wore the ActiGraph sensor was their dominant or non-dominant side. The main steps for data processing to estimate the activity and sleep measurement variables are illustrated in Figure 4.2.

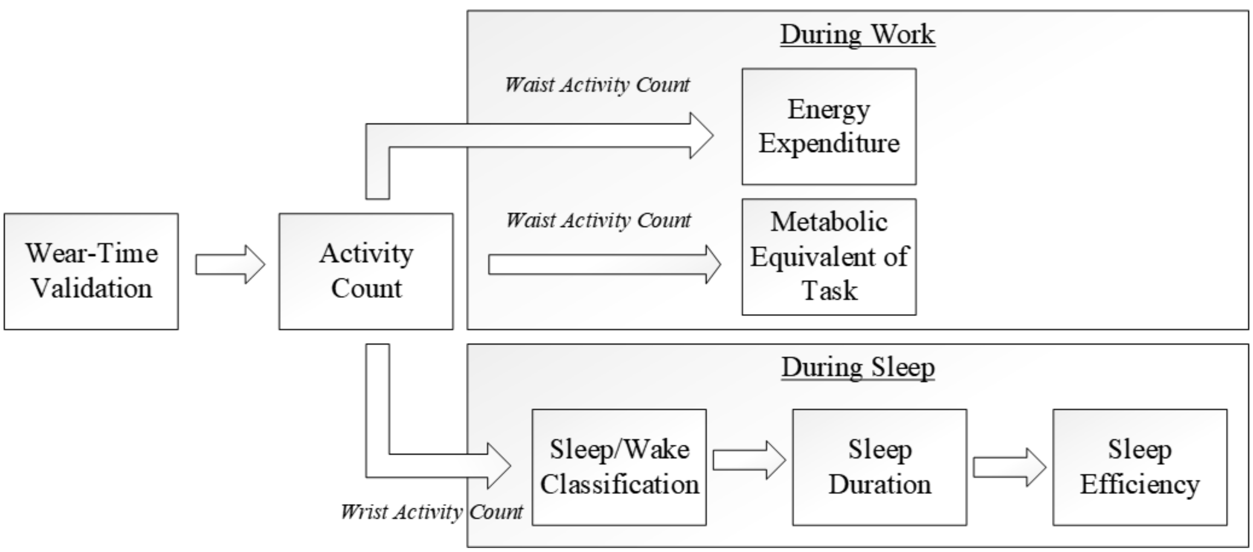

Figure 4.2 Steps for data processing in ActiLife

For wear time validation in the ActiLife software, an algorithm introduced by Choi, Liu, Matthews, and Buchowski (2011) was selected to calculate wear time by classifying accelerometer wear and non-wear time intervals in the raw accelerometer data. Table 4.2 summarizes the algorithms utilized in ActiLife for processing the raw accelerometer data collected from ActiGraph sensors to estimate activity counts.

Table 4.2 Algorithms applied in ActiLife data analysis for measuring counts (adapted from Lee et al., 2017a)

Description	Algorithm	Notes	Reference
Wear time detection	Definition of a non-wear period • Minimum length = 90 minutes • Small window length = 30 minutes • Spike tolerance = 2 minutes	Utilizes vector magnitude counts	Choi et al. (2011)
Unit of activity measure	Total vector magnitude counts, which count activities that exceeded the threshold (= 0.001664g) of the vector sum estimated by $\sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2}$, where A_x is x-axis acceleration, A_y is y-axis acceleration, and A_z is z-axis acceleration. Wrist counts per minute scaled down for waist counts 1) If wrist counts are between 0 and 644, • CPM * = 0.5341614 × wrist count 2) If wrist counts are between 645 and 1272, • CPM = 1.7133758 × wrist count – 759.414013 3) If wrist counts are between 1272 and 3806, • CPM = 0.39997632 × wrist count + 911.501184 4) If wrist counts are greater than or equal to 3807, • CPM= 0.0128995 × wrist count +2383.904505	Scaled for wrist-worn device in ActiLife	ActiGraph (2012; 2016b; 2016c)

* CPM: Counts per minute adjusted to waist scale

ActiLife was utilized to estimate a subject's EE score based on the Freedson combination energy expenditure algorithm (Freedson et al., 1998) by combining Williams's work energy formula (Williams, 1998) and Freedson's empirical energy expenditure prediction equation (Freedson et al., 1998). The METs were calculated utilizing Swartz's Adult Overground and Lifestyle algorithm (Swartz et al., 2000). The gold-standard measurement method for EE and MET is the dual-labeled water method (Ainslie, Reilly, & Westerterp, 2003; Besson, Brage, Jakes, Ekelund, & Wareham,

2010) and ActiGraph demonstrated excellent effectiveness and reliability in comparative studies based on standard measurements by the gold-standard method (Rothney, Brychta, Meade, Chen, & Buchowski, 2010; Kinnunen, Tanskanen, Kyröläinen, & Westerterp, 2012). EE and MET measurements for waist-worn ActiGraph sensors are considered to be a validated method (ActiGraph, 2012). Therefore, the ActiLife software provides the adjusted scale for EE and MET based on a wrist-worn ActiGraph sensors (ActiGraph, 2012). Table 4.3 summarizes the algorithms utilized in ActiLife for estimating energy expenditure variables from the activity counts data described in Table 4.2.

Table 4.3 Algorithms applied for energy expenditure variables from ActiGraph sensors worn on the wrist (adapted from Lee et al., 2017a)

Description	Algorithm	Notes	Reference
Energy expenditure	Kcals [*] = CPM [*] × 0.0000191 × BM	Adult aged 19 and older	Williams (1998)
	If CPM > 1951 then, • kcals/min = 0.00094 × CPM + (0.1346 × BM [*] – 7.37418)	Calibrated internal scale of ActiLife	Freedson et al. (1998)
	If CPM > 1951 then, • kcals/min = [0.00094 × CPM + (0.1346 × BM – 7.37418)] else, • kcals/min = CPM × 0.0000191 × BM	Combination of Williams (1998) and Freedson et al. (1998)	ActiGraph (2016d)
Metabolic equivalent of task	MET Rate = 2.606 + (0.0006863 × CPM)		Swartz et al. (2000)

[*] CPM: Counts per minute adjusted to waist scale; BM: Body mass in kilogram; kcals: Total calories for a single epoch

The Cole-Kripke algorithm (Cole, Kripke, Gruen, Mullaney, & Gillin, 1992) was selected to detect sleeping or awake states based on wrist activity scores. Then, the Tudor-Locke algorithm (Tudor-Locke, Barreira, Schuna, Mire, & Katzmarzyk, 2013) provided by ActiLife was utilized for estimating sleep durations based on the time periods during which a subject was “in bed” or “out of bed," which were calculated based on the sleeping/awake identification by the Cole-Kripke algorithm. The internal algorithm of ActiLife, which was verified on an adult population, was utilized to estimate sleep efficiency as an indicator of sleep quality. The sleep fragmentation index (SFI) was calculated by utilizing the internal algorithm of ActiLife to quantify restlessness during sleep. A higher SFI indicates that a subject's sleep was more disrupted. Table 4.4 summarizes the algorithms utilized in ActiLife for estimating sleep variables based on data collected from ActiGraph sensors.

Table 4.4 Algorithms applied to sleep variables from ActiGraph sensors worn on wrist (adapted from Lee et al., 2017a)

Description	Algorithm	Notes	Reference
Sleeping/awake identification	D = 0.00001(550$_{A-4}$ + 378$_{A-3}$ + 413$_{A-2}$ + 699$_{A-1}$ + 1736$_{A0}$ +287$_{A+1}$ + 309$_{A+2}$), where D is the sleeping/awake identification; A_i = Activity score at time *i*; and A_0 is the present time and the interval of *i* is 1 minute. If D < 1, • D is identified as "Sleep". Else, • D is identified as "Wake".	Wrist activity score	Cole et al. (1992)
Sleep periods estimated from in-bed and out-of-bed times	• In-bed time: 5 consecutive sleeping minutes • Out-bed time: 10 consecutive awake minutes after sleeping • Minimum amount of time between in-bed time and out-bed time: 160 minutes	Calibrated internal scale of ActiLife for wrists	Tudor-Locke et al. (2013)
Quantified quality of sleep	Sleep efficiency (%) = (Number of sleep minutes / total number of minutes in bed estimated from the difference of in-bed and out-bed time) × 100		ActiGraph (2012)
Sleep fragmentation index	The sum of movement index (MI) and fragmentation index (FI) • MI = [Total time scored awake (in minutes) / (Total time in bed (in hours) × 100 • FI = (Total of 1 minute scored sleep bouts / Total number of sleep bouts of any length) × 100		ActiGraph (2018)

* CPM: Counts per minute adjusted to waist scale; BM: Body mass in kilogram

4.2 Data Preprocessing

Statistical tests to confirm the normality of the data were conducted utilizing the Shapiro-Wilk and adjusted Kolmogorov-Smirnov tests, which are the most common methods for statistical testing of normality (Hair, Black, Babin, Anderson, & Tatham, 2006). The hypotheses for the normality test were as follows: (1) null hypothesis: the distribution of the population follows a normal distribution or (2) alternative hypothesis: the distribution of the population does not follow a normal distribution. Both the Kolmogorov-Smirnov and Shapiro-Wilk tests were performed with a significance threshold of 0.05 utilizing the SPSS version 23 software (SPSS Inc., Chicago, IL, USA). If the null hypothesis was rejected at a significance level of 0.05, then the variables were not considered to follow a normal distribution. Because of the low power of the Kolmogorov-Smirnov test, the Shapiro-Wilk test is recommended for small sample sizes (Ghasemi & Zahediasl, 2012). Therefore, the final data transformation (a logarithmic transformation) decision was made based on the results of the Shapiro-Wilk test. The parameters utilized as a reciprocal scale (e.g., "1" over the original value) in the data analysis did not require a logarithmic transformation because the inverse values of these parameters tended to be normally distributed.

4.3 Structural Equation Modeling

SEM, which allows researchers to test interrelated research questions and theoretical models with all possible information, is an extension of various multivariate techniques, including factor analysis and multiple regression analysis (Hair et al., 2006). Multivariate regression analysis is limited to identifying a series of relationships between independent variables and dependent variables (Hair et al., 2006). It only allows researchers to estimate a single relationship between an independent variable and dependent variable. Therefore, it is not a suitable solution for completely revealing the relationships between concepts to understand real phenomena (Hair et al., 2006). SEM is a combined form of factor analysis and regression analysis for causal relationship analysis (Hair et al., 2006). Based on a theoretical background, SEM seeks to explain potential relationships between measurement variables and tests hypotheses regarding the relationships between research constructs (Hair et al., 2006). Confirmatory factor analysis is an important part of conventional structural equation modeling (Hair et al., 2006). Confirmatory factor analysis is utilized when there is either preliminary knowledge or theoretical results for the variables to be analyzed from existing research theories or empirical research results (Hair et al., 2006). The main benefits of SEM are the ability to choose to reflect measurement errors that can occur during research processes, such as simple data entry errors, and define latent constructs that can be incorporating into analysis (Hair et al., 2006). For our current dissertation research, SEM is the most applicable data analysis method because of the presence of latent constructs in the proposed model, as indicated in Figure 4.3. Latent variables, such as task demands, are not directly measurable, whereas a heart rate indicator can be measured directly utilizing heart rate monitors (Figure 4.3).

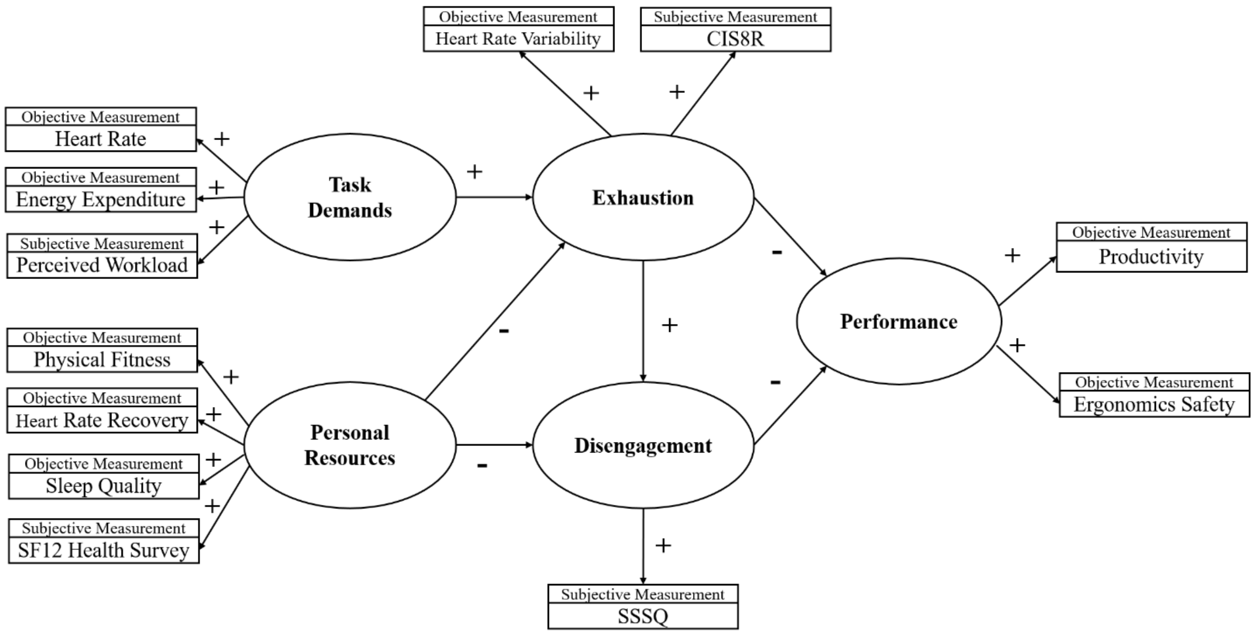

Figure 4.3 Structural equation model for job characteristics, burnout, and performance (proposed measurement and structural models)

4.3.1 Covariance-based Structural Equation Modeling versus Partial Least Squares Structural Equation Modeling

SEM analysis is conducted as CB-SEM to verify a research model. SEM is commonly referred to as covariance structure analysis, covariance structure modeling, or analysis of covariance structures (Kline, 2015) because CB-SEM aims to minimize the difference between the model covariance matrix and model predictive matrix obtained from data, whereas statistical techniques tend to focus on individual cases. The CB-SEM method is utilized to estimate parameters based on a maximum likelihood function and minimize the difference between sample covariance and the covariance predicted by a research model (Chin & Newsted, 1999). For CB-SEM, there are strict guidelines for the minimum number of sample sizes required for SEM analysis. Hair et al.

(2006) suggested that the minimum sample size can be determined based on the characteristics of the measurement model and model complexity. CB-SEM methods have been widely utilized in construction engineering and management research. For example, Molenaar, Washington, and Diekmann (2000) developed a construction contract dispute prediction model to investigate the interrelationships between contract dispute potential, owner management ability, contractor management ability, risk allocation, and project scope definition utilizing CB-SEM with 252 samples collected from a survey. Chen, Dib, Cox, Shaurette, and Vorvoreanu (2016) identified the three key causal factors of technology management, process management, and information management that are associated with building information modeling maturity by applying CB-SEM with 249 samples.

Another approach for SEM analysis is utilizing the PLS-SEM method as an alternative approach to the CB-SEM method. PLS-SEM is a nonparametric approach that does not strictly account for assumptions regarding data distributions (Hair, Hult, Ringle, & Sarstedt, 2017). For a complex model, PLS-SEM requires a relatively small number of samples compared to CB-SEM (Nitzl, 2016). Hair et al. (2017) stated that PLS-SEM can achieve marginally greater statistical power than CB-SEM. The PLS-SEM method has an exploratory nature, whereas the CB-SEM method has a confirmatory nature based on confirmed theories (Hair et al., 2017). The PLS-SEM algorithm maximizes the explained variance of endogenous variables and estimates parameters in terms by minimizing measurement errors and residuals (Hair et al., 2017). Rather than calculating latent variables simultaneously for all models, parameters are calculated by dividing the parameters into blocks based on latent variables, hence the use of the term “partial” (Lee, Petter, Fayard, & Robinson, 2011). The estimation method in PLS-SEM is different from the maximum likelihood estimation method in CB-SEM. PLS-SEM is a methodology based on classical least-squares regression analysis for estimating parameters and minimize the difference between a model prediction matrix and sample matrix (Henseler, Hubona, & Ray, 2016).

Unlike CB-SEM, fitting measures such as chi-square (χ^2), root mean squared error of approximation, and incremental fix index for evaluating the elements an overall model cannot be applied in PLS-SEM. Therefore, PLS-SEM path modeling utilizes the predictive capabilities of the model as the criteria to assess model quality (Hair et al., 2017). Although PLS-SEM does not require a large sample sizes (compared to CB-SEM), its sample size should be sufficient to satisfy the "10-times rule" proposed by Barclay, Higgins, and Tompson (1995). This rule states that the minimum sample size should be equivalent to (1) 10 times the greatest number of formative indicators measured for a single construct or (2) 10 times the greatest number of construct paths that lead to a specific construct in a structural model (Barclay et al., 1995).

4.3.2 Selection of Data Analysis Methods between CB-SEM and PLS-SEM

Both CB-SEM and PLS-SEM were considered when selecting an analytical approach for evaluating our structural model. PLS-SEM was eventually selected in this dissertation study over CB-SEM based on the following characteristics and the objectives of the research. Previous studies (e.g., Lee et al. 2017a) indicated that several physiological measurements did not represent a normal distribution and preliminary data analysis in our research found the same results of non-normal distributions in sensor data. PLS-SEM does not make assumptions regarding data distributions because it is a nonparametric approach, meaning it does not assume a normal distribution of data (Hair et al., 2017). When the sample size of data is small, PLS-SEM analysis is recommended for its high efficiency in parameter estimation and greater statistical power (Hair et al., 2017). This benefit was also the major reason why other researchers chose PLS-SEM in management information systems research (Ringle, Sarstedt, & Straub, 2012). The PLS-SEM method has been adopted in studies with sample sizes of less than 100 in the field of management information systems research (Liang, Saraf, Hu, & Xue, 2007; Bhattacherjee & Sanford, 2006). Urbach and Ahlemann (2010) recommend a minimum range of sample sizes between 30 and 100 for the use of PLS-SEM. The 80 samples in this dissertation study meet this criterion. Marketing research articles published in the 30 top-ranked journals, including an article by Hair, Sarstedt, Ringle, and Mena (2012), found that researchers frequently selected PLS-SEM because of small sample sizes. Although the covariance-based approach is the focus of confirmation for theoretical models, PLS-SEM is known to be suitable more for exploratory studies (Hair et al., 2017). This study is based on a theoretical model that is well formed based on existing literature and aimed at theory testing based on a series of hypothesis tests. However, the ultimate goal of this dissertation study is to evaluate the performance of endogenous prediction utilizing the proposed model. Therefore, this research has an exploratory nature when it comes to predicting safety indicators in terms of tasks and individual-level productivity utilizing the job demands-resources model, as well as identifying whether or not the construct defining short-term burnout acts as a driver for predicting construction worker performance. In the case of CB-SEM, there was a concern regarding model identification issues (Hallak & Assaker, 2016) because of the constraints of complex measurement models. Testing the complexity of a model is easier and model identification is not problematic in PLS-SEM (Rigdon, 2014). The sensor measurements utilized in this study potentially contain random errors. Therefore, the application of PLS-SEM is logical (Anderson & Gerbing, 1988; Henseler et al., 2016).

PLS-SEM has recently been actively utilized in construction management research (e.g., Brunetto, Xerri, & Nelson, 2013; Song, Migliaccio, Wang, & Lu, 2017) and occupational health research (e.g., Yassaee & Mettler, 2017). Lim and Loosemore (2012) utilized PLS-SEM to identify the factors that predict the organizational flexibility of construction firms. Doloi (2014) analyzed a theoretical structural model utilizing PLS-SEM to understand the impact of web-based systems on the performance of construction projects. Utilizing PLS-SEM, Zhang and Qian (2017) analyzed how contractor performance risk perceptions and relationship risk perceptions act as mediators between an owner's mediated power and contractor opportunism, and how solidarity acts as a moderator. Song et al. (2017) utilized the PLS-SEM method to evaluate the effect of top-management mediation on various factors, such as system quality, information quality, and external services related to building information by modeling user satisfaction. Aibinu and Al-Lawati (2010) applied PLS-SEM to test a research model to understand the relationships between various factors, including security, user friendliness, cost, resources, perceived benefits and barriers, and willingness to participate in e-bidding at the organizational level. PLS-SEM was also recommended in construction management research studies conducted by Aibinu and Al-Lawati (2010), Ling, Li, Low, and Ofori (2012), and Zhao and Singhaputtangkul (2016) because of their small sample sizes. For the reasons summarized in Table 4.5, PLS-SEM was selected in this this dissertation study as our data analysis method. SmartPLS 3.0 (Bönningstedt, Germany, SmartPLS GmbH) was chosen as a PLS-SEM platform in this study.

Table 4.5 Selection criteria to decide between CB-SEM and PLS-SEM (adapted from Hair et al., 2017)

Covariance-based structural equation modeling (CB-SEM)	Partial least squares structural equation modeling (PLS-SEM)
• Theory testing and theory confirmation • Large sample sizes • Circular relationships • Global goodness-of-fit criterion • Normally distributed data	• Explanatory studies • Prediction of key target constructs • Complex structural models • Small sample sizes • Non-normally distributed data

4.3.3 Selection between Reflective Measurement Model and Formative Measurement Model

Depending on the relationships between the latent variables and measurement variables, either the reflective measurement model or formative measurement model can be selected for PLS-SEM (Hair et al., 2017). The reflective model assumes that the construct is the main cause of indicator variable measurements, whereas the formative model assumes that indicator variables are the main cause for the construct, as indicated in Figure 4.4 (Hair et al., 2017). PLS-SEM does not place a restriction on the computation of a model that includes both reflective and formative indicators (Diamantopoulos & Winklhofer, 2001).

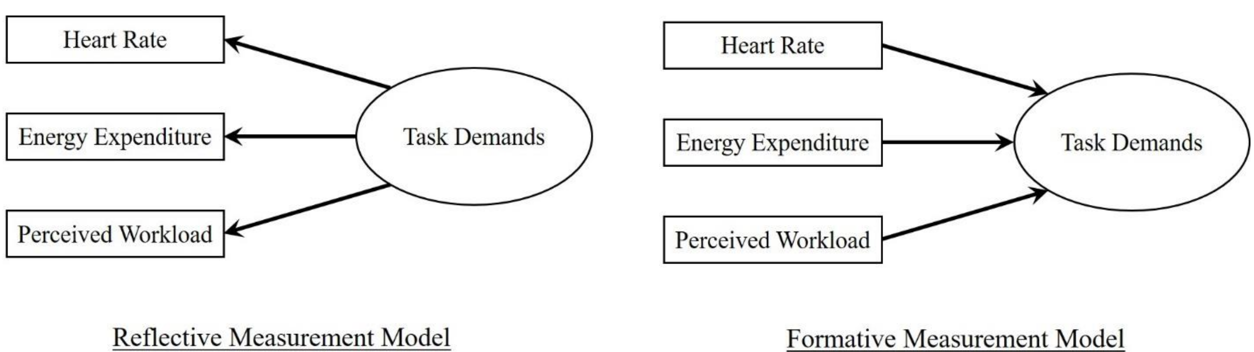

Figure 4.4 Comparison between formatively measured construct and reflectively measured construct

Because the indicators represent results that are not the cause of the construct, this study adopted the reflective model and its corresponding measurement model mode (Rossiter, 2002). Both exogenous (independent latent variables) and endogenous constructs (dependent latent variables) were modeled as reflective measurement models.

4.4 Two-step Process of PLS-SEM

The PLS-SEM process does not include global goodness-of-fit criteria for assessing models, such as that provided in CB-SEM (Henseler, Ringle, & Sinkovics, 2009). Therefore, for PLS-SEM analysis, a two-step process including outer model assessment and inner model assessment was utilized, similar to the study by Chin (1998). PLS-SEM follows a two-step process to assess partial model structures: (1) assessment of the measurement model and (2) assessment of the structural model (Henseler et al., 2009). A graphical summary of this two-step process is illustrated in Figure 4.5.

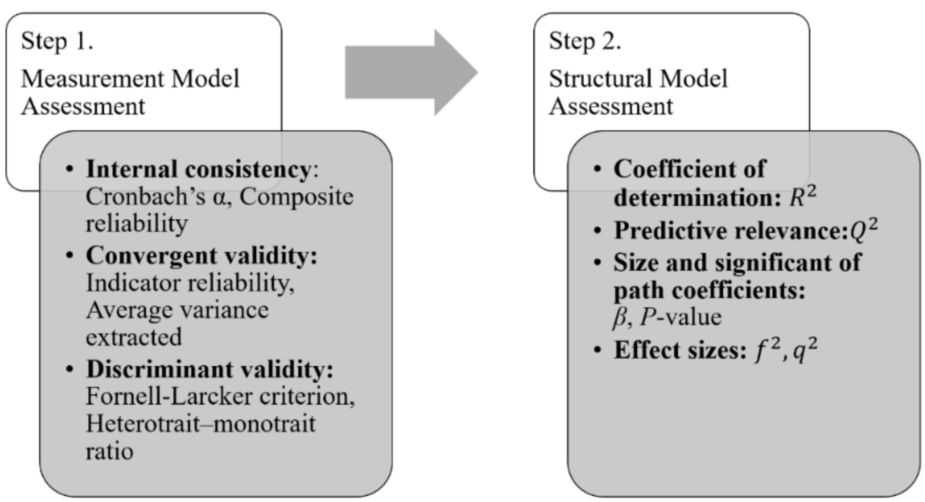

Figure 4.5 Systematic two-step process of PLS-SEM for reflective measurement models (adapted from Hair et al., 2017)

4.4.1 Measurement Model

Evaluation of the reflective measurement model was based on internal consistency utilizing Cronbach's α and composite reliability. Furthermore, convergent validity was evaluated based on indicator reliability and the calculation of average variance extracted (AVE). Finally, discriminant validity utilizing the Fornell-Larcker criterion and Heterotrait-monotrait ratio (HTMT) was also estimated for assessing the reflective measurement model (Hair et al., 2017). As an indicator of internal consistency, Cronbach's α is estimated by utilizing equation 4.5 (Hair et al., 2017):

$$Cronbach's\ \alpha = \left(\frac{M}{M-1}\right)\left(1 - \frac{\sum_{i=1}^{M} S_i^2}{S_t^2}\right) \tag{4.5}$$

where M is the number of indicators, S_i^2 is the variance of the indicator variable i of a specific construct, and S_t^2 is the variance of the sum of all M indicators of the construct. If Cronbach's α is greater than 0.7, then a model is generally considered appropriate in terms of internal consistency (Hair et al., 2017).

Composite reliability (CR) is calculated by dividing the square of the total standardization coefficient by the square of the total standardization coefficient for the sum of errors (Hair et al., 2017). CR is the index utilized to determine the overall reliability of observed variables (Hair et al., 2017). Typically, CR should be higher than 0.7. However, CR values between 0.60 and 0.70 are considered to represent acceptable internal consistency reliability for exploratory research

(Hair et al., 2017). The formula for calculating CR based on the study by Chin (1998) can be expressed as follows:

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \sum_{i=1}^{n} var(\varepsilon_i)} \qquad (4.6)$$

where λ_i is the component loading of each item to a latent variable and $\varepsilon_i = (1 - {\lambda_i}^2)$.

Indicator reliability can be assessed based on the absolute standardized outer loadings that represent the absolute correlation between a construct and its measurement variables (Henseler et al., 2009). An indicator's outer loadings must be greater than 0.70 (Hair et al., 2017). An indicator with an outer loading between 0.40 and 0.70 must be removed from the measurement model when the elimination of indicators increases the AVE (discussed below) (Hair et al. 2017). If the outer loadings are less than 0.4, the reflective indicators should be removed from the measurement model (Churchill, 1979).

Convergent validity can also be assessed utilizing the AVE that corresponds to the communality of a construct (Hair et al., 2017). This AVE is calculated by utilizing equation 4.6 based on the study by Chin (1998):

$$AVE = \frac{\sum_{i=1}^{n} ({\lambda_i}^2)}{\sum_{i=1}^{n} ({\lambda_i}^2) + \sum_{i=1}^{n} var(\varepsilon_i)} \qquad (4.6)$$

where λ_i is the component loading of each item to a latent variable and $\varepsilon_i = (1 - {\lambda_i}^2)$. AVE indicates the volume of variance from the construct in relation to the volume of variance from measurement deviation (Hair et al., 2017). Convergent validity is supported when the AVE is greater than 0.5 (Fornell & Larcker, 1981).

Discriminant validity is based on empirical criteria indicating whether or not a construct is distinct from other constructs (Hair et al., 2017). Satisfactory discriminant validity implies that a construct is independent of other constructs in the model and not explained by other constructs (Hair et al., 2017). For evaluating discriminant validity, the cross loading of indicators was assessed as an initial approach (Hair et al., 2017). The outer loading of one indicator associated with a construct must be greater than all the cross loads associated with the other constructs (Hair et al., 2017). To satisfy discriminant validity, the outer loading of the indicator corresponding to the construct must be greater than the cross loading values of the other constructs (Henseler et al., 2009).

The Fornell-Larcker criterion (Fornell & Larcker, 1981), which is another measure for evaluating discriminant validity, was also calculated. This method compares the square root of each construct's AVE value to that construct's correlation value. According to the Fornell-Larcker criterion, the square root of the AVE of each construct must be greater than the largest correlation value between other constructs (Hair et al., 2017). HTMT is another criterion utilized to assess discriminant validity (Henseler, Ringle, & Sarstedt, 2015). HTMT estimates the correlation between two constructs when the two constructs in question are perfectly reliable (Hair et al., 2017). The confidence interval of HTMT from bootstrap analysis should not include the value "1," meaning it is acceptable for discriminant validity analysis (Hair et al., 2017). Furthermore, all HTMT values should be lower than 0.85 (Kline, 2015). Table 4.6 summarizes the measurement model assessment criteria discussed in this section.

Table 4.6 Assessment criteria for reflective measurement model

Index	Measurement model assessment criteria	Reference
Internal consistency		
1. Cronbach's α	Greater than 0.7	Hair et al. (2017)
2. Composite reliability	• Greater than 0.7 • CR values between 0.60 and 0.70 are considered to be acceptable for exploratory research	Hair et al. (2017)
Convergent validity		
1. Indicator reliability	• Outer loadings must be greater than 0.70 • Outer loadings between 0.40 and 0.70 must be removed from the measurement model when the elimination of indicators increases AVE • Outer loadings less than 0.4 should be removed	Churchill (1979); Hair et al. (2017)
2. Average variance extracted (AVE)	Greater than 0.5	Fornell & Larcker (1981)
Discriminant validity		
1. Cross-loadings	The outer loading of one indicator associated with a construct must be greater than all the cross loads associated with other constructs.	Hair et al. (2017); Henseler (2009)
2. Fornell-Larcker criterion	The square root of the AVE of each construct must be greater than the highest correlation value among other constructs.	Hair et al. (2017)
3. Heterotrait-monotrait ratio (HTMT)	• The confidence interval of HTMT from the bootstrap analysis should not include the value "1." • HTMT values should be lower than 0.85.	Hair et al. (2017); Kline (2015)

4.4.2 Structural Model

Because the structural model in this study does not include formatively measured constructs, potential collinearity issues (i.e., high correlations between two formatively measured indicators) were tested based on the Fornell-Larcker criterion (a variance inflation factor was not computed in the current study) utilized during the measurement model evaluation process (Hair et al., 2014). The statistical significance of the path coefficients (β) was calculated utilizing Efron's (1987) bias-corrected and accelerated bootstrapping resampling method. Bootstrapping was utilized to reconstruct a subsample from the raw data. The 5,000 minimum bootstrap samples recommend by Hair et al. (2017) were utilized for analysis. To obtain a robust estimate of the confidence intervals in a population, bootstrapping performs random sampling with replacement from the original samples. The significance of all path coefficients were assessed via bootstrapping with 5,000 subsamples in the study by Hair et al. (2017). In our research, the bootstrapping procedure was conducted for 80 cases with 5,000 bootstrap samples utilizing the SmartPLS 3.0 software. In other words, during bootstrapping, 5,000 subsamples were reconstructed from the original 80 sample data. The random sampling of observations was performed with replacement and returned selected samples back to the sampling population before sampling the next observation (Hair et al., 2017). Any of the original samples may or may not be selected at least once for bootstrapping (Hair et al., 2017).

The standard error of the measured coefficients was calculated via bootstrapping. If the calculated t value was greater than the reference t value (two-tailed) at the selected significance level (e.g., alpha level = 0.10; 0.05; 0.01), then the coefficient was significantly different from zero, meaning the outer loadings were significant at the selected significance level (Hair et al., 2017). PLS-SEM can determine the magnitude of the direct and indirect effects of latent variables included in a model (Hair et al., 2017). Direct effects refer to a variable having a direct effect on another variable and indirect effects are the effects between two variables being mediated by a third variable (Hair et al., 2017). Therefore, the total effect is the sum of the direct and indirect effects of one latent variable on another.

Next, the coefficient of the determinant (R^2), predictive relevance (Q^2), and effect sizes (f^2 and q^2) were estimated. The most commonly used measure for the evaluation of PLS models is the coefficient of the determinant (R^2). It measures the accuracy of predictions from a model and is calculated based on the square of the correlations between the actual and predicted values of a particular endogenous variable (Hair et al., 2017). R^2 estimates were calculated for all endogenous constructs. Based on the study by Chin (1998), the R^2 values for the endogenous constructs can be classified as substantial (greater than 0.67), moderate (greater than 0.33 and less than 0.67), or weak (greater than 0.19 and less than 0.33).

Adding an additional exogenous construct simply increases the R^2 of the existing endogenous constructs (Hair et al., 2017). The adjusted coefficient of determination $R^2_{adjusted}$ is a modified R^2 value based on the exogenous construct related to the number of samples, which compensates for the fact that a complex model increases the value of R^2 (Hair et al., 2017). According to Hair et al. (2017), $R^2_{adjusted}$ can be estimated by utilizing equation 4.7:

$$R^2_{adjusted} = 1 - (1 - R^2) \times \frac{n-1}{n-k-1} \tag{4.7}$$

where *n* is the number of samples and *k* is the number of exogenous latent variables utilized to predict the endogenous latent variables. In order to compare the PLS-SEM analysis results of models with different numbers of samples and/or different numbers of exogenous constructs, $R^2_{adjusted}$ values are compared (Hair et al., 2017).

The f^2 value is computed to analyze the change in R^2 when a specific construct is excluded from a structural model. The f^2 effect size is calculated by utilizing equation 4.8 (Hair et al., 2017):

$$f^2 = \frac{(R^2_{included} - R^2_{excluded})}{1 - R^2_{included}} \tag{4.8}$$

where $R^2_{included}$ and $R^2_{excluded}$ are the R^2 values of the endogenous latent variable when the selected latent variable is included or removed from the model, respectively. f^2 values of 0.02, 0.15, and 0.35 indicate that the effect sizes of the excluded exogenous constructs are small, medium, and large, respectively (Cohen, 1988).

As an index of predictive relevance, cross-validated redundancy (Q^2) was also estimated. To evaluate predicted relevance, blindfolding to measure the cross-validated redundancy of each endogenous construct was performed. The details of the blindfolding process are described in the next chapter of this dissertation for the comparison of Q^2 values between the survey model, sensor model, and combined model. The Q^2 values were validated according to method proposed by Geisser (1974) and it was confirmed that these values are greater than zero. A value of Q^2 greater than zero indicates the predictive relevance of the path model in the construct. However, it does not represent the quality of prediction (Rigdon, 2014).

Relative measures of predictive relevance are comparable through the measurement of q^2 effect sizes and are calculated by utilizing equation 4.9 (Hair et al., 2017):

$$q^2 \ effect\ size = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}} \tag{4.9}$$

where $Q^2_{included}$ and $Q^2_{excluded}$ are the Q^2 values of the endogenous latent variable when the selected extrinsic latent variable is included or removed from the model, respectively. As relative criteria for predictability, values of 0.02, 0.15, and 0.35 indicate that exogenous constructs have small, medium, and large predictive relevance for other specific endogenous constructs, respectively (Henseler et al., 2009).

Chapter 5 Results

This chapter summarizes descriptive statistics, hypothesis testing results, analysis of prediction accuracy, and relevance of models from the data analysis. Section 5.1 summarizes the descriptive statistics for subject demographic information and for measurement variables. Section 5.2 presents the results of the measurement model and a structural model assessment of the research model. Section 5.3 summarizes the moderating effect of personal resources on the relationship between task demands and exhaustion in the proposed model. Section 5.4 presents the results of the mediation effect of burnout between task demands and performance constructs or between personal resources and performance constructs.

5.1 Demographic Information of Subjects

The unit of analysis of this study comprises individual, entry-level construction workers. A total of 22 subjects, comprising trainees from the pre-apprenticeship program and university students, participated in multiple experiments designed to expose subjects to different levels of task demands and recorded different levels of personal resources. As Charness, Gneezy, and Kuhn (2012) stated, the economic factor in the subject recruitment influenced their decision to design the repeated measurements experiment. For the same reason, the current study also designed the repeated measurements experiment. The subjects participated in four experimental sessions in which they were exposed to various task demands and personal resource levels; thus, the indicators measured by sensors and survey instruments varied within the data collected in different experimental sessions from the same subjects. The order of experimental sessions was randomly assigned to the subjects, and there was at least a one-week interval between the scheduled experimental sessions. The subjects' age, height, weight, and gender were not directly used as indicators to measure the research construct in the model. The non-varied variables within the same subjects (e.g., age) were only used as basic inputs to estimate the subjects' physiological and physical activity measurement data (e.g., energy expenditure and relative heart rate). Therefore, the data points obtained during each experimental session were considered independent observations. The demographic information of the subjects is summarized in Table 5.1. The information on age, height, and weight were obtained from surveys conducted during the recruitment of subjects; the subjects provided their consent prior to data collection. Body mass index (BMI) was calculated based on height and weight information. The percentage of male and female subjects were 64% and 36%, respectively. Of the observations collected, 18% were pre-apprenticeship program trainees, and 82% were university students.

Table 5.1 Demographic Characteristics (n=22)

Characteristic		Mean	SD	Min	Max
Age (years)		25.0	3.00	22	34
Height (meters)		1.7	0.08	1.6	1.88
Weight (kg)		70.1	14.03	49	100
Body mass index		23.4	3.50	18.4	30.4
		N	%		
Gender					
	Male	14	64		
	Female	8	36		
Type of subject					
	Pre-Apprenticeship program trainee	4	18		
	University student	18	82		

The names and detailed descriptions of the measurement variables used in the data analyses are listed in **Appendix A**. As described in **Appendix A**, the measurement variable td_Inversedp is the inversed scale of the NASA task load index (TLX) for the performance subscale. While the other

NASA-TLX items (i.e., td_Physicald, td_Temporald, td_Mentald, td_Effort, and td_Frustrationl) put a high task load on each subscale if the score is high, the performance scale starts with a low score (a good score), and a high score is considered a poor result. Therefore, this converts to an inverse scale, as used in the data analysis. In terms of the indicator of performance in **Appendix A**, pf_Ergo60, the riskiest classification for trunk flexion in the rapid upper limb assessment (RULA) and rapid entire body assessment (REBA) methods, uses the 60-degrees threshold (McAtamney & Corlett, 1993; McAtamney & Hignett, 2000). Therefore, if the trunk flexion is greater than 60 degrees in the data point collected at 10Hz, it is classified as the non-neutral posture.

The descriptive statistics of the measurement variables are summarized in Tables 5.2 through 5.6. It also summarizes the results of the statistical tests that were conducted to verify the normality of the data, analyzing the skewness and kurtosis of each variable to find outliers. When data presented a significant skewness or kurtosis, data transformations (e.g., natural log transformation and inverse transformation for non-zero data) were conducted for the partial least squares structural equation modeling (PLS-SEM) analysis. For example, the heart rate variability measurements (e.g., eh_Sdnn and eh_Rmssd) were found to deviate excessively from the normal distribution because both the skewness and kurtosis deviated significantly from 0. Thus, inverse transformation was applied to convert the data and make them normally distributed before the data could be used in the PLS-SEM analysis. The descriptive statistics of the measurement variables by the type of subject (i.e., trainees from the pre-apprenticeship program versus university students) are summarized in Tables B.1 through B.5 in **Appendix B**.

Table 5.2 Descriptive statistics (Task demands indicators, n=80)

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
td_Hrbpm	0	113.8	111.8	79.3	162.4	18.89	-0.347	0.366
td_Rhr	0	36.2	35.7	15.2	79.5	14.14	0.317	0.837
td_Enerkcal	0	185.3	196.2	33.1	404.4	85.20	-0.751	0.048
td_Enermet	0	3.6	3.6	1.5	5.0	0.64	0.332	-0.382
td_Wenerkcal	1	158.5	160.0	63.6	360.6	67.40	0.452	0.723
td_Wenermet	1	3.5	3.6	2.7	4.1	0.23	1.392	-0.487
td_Rtlx	0	9.125	9.3	4.167	14.7	2.52	-0.802	0.144
td_Physicald	0	11.8	12.0	1.0	19.0	4.71	-0.394	-0.520
td_Temporald	0	7.8	7.0	1.0	18.0	4.56	-1.061	0.207
td_Mentald	0	4.85	4.0	1.0	17.0	3.67	1.516	1.368
td_Effort	0	10.5	10.0	2.0	20.0	4.44	-0.800	-0.030
td_Frustrationl	0	4.9	3.0	1.0	19.0	4.60	0.644	1.263
td_Inversedp	0	14.9	17.0	5.0	20.0	4.72	-0.608	-0.831

Table 5.3 Descriptive statistics (Personal resources indicators, n=80)

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
pr_Resthr	0	70.1	69.5	44.2	94.5	11.38	-0.482	-0.036
pr_Smwt	0	534.8	539.0	445.7	629.7	41.88	-0.365	-0.118
pr_Hrr	2	17.6	15.2	0.5	42.2	11.75	-0.626	0.609
pr_Sf12pcs	0	55.8	56.4	42.7	66.7	4.70	0.657	-0.723
pr_Sf12mcs	0	51.4	53.7	31.3	62.3	7.57	0.396	-1.091
pr_Sf12tot	0	53.6	55.2	42.7	59.4	4.13	0.077	-0.989
pr_Pfnbs	0	55.6	57.3	41.5	57.3	4.27	5.273	-2.524
pr_Rpnbs	0	53.2	57.1	40.2	57.1	5.00	-0.236	-0.952
pr_Bpnbs	0	52.9	57.0	19.0	57.0	7.62	6.671	-2.466
pr_Ghnbs	0	57.0	57.8	34.5	63.6	6.49	1.879	-1.278
pr_Sleepqual	3	83.5	84.3	62.0	97.6	6.48	1.040	-0.688
pr_Totalsleep	3	340.5	332.0	106.0	788.0	97.39	5.806	1.412
pr_Sfi	3	28.4	26.9	4.8	60.2	11.77	0.596	0.688

Table 5.4 Descriptive statistics (Exhaustion indicators, n=80)

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
eh_Cis	0	23.5	24.0	8.0	40.0	6.72	-0.352	0.023
eh_cisitem1	0	4.1	4.0	1.0	7.0	1.80	-1.213	-0.076
eh_cisitem2	0	3.8	4.0	1.0	7.0	1.80	-1.151	-0.193
eh_cisitem3	0	2.9	3.0	1.0	7.0	1.60	-0.182	0.683
eh_cisitem4	0	2.1	2.0	1.0	6.0	1.30	1.174	1.374
eh_cisitem5	0	4.5	4.0	1.0	7.0	1.64	-0.705	-0.188
eh_cisitem6	0	1.8	1.0	1.0	6.0	1.04	3.126	1.651
eh_cisitem7	0	2.0	2.0	1.0	6.0	1.01	2.052	1.226
eh_cisitem8	0	2.3	2.0	1.0	6.0	1.18	0.207	0.764
eh_Sdnn	0	45.9	45.0	8.9	97.1	21.08	-0.655	0.251
eh_Rmssd	0	21.5	21.2	5.1	48.7	10.74	-0.581	0.419
eh_Hrvlffft	0	2,222.8	1,619.8	47.5	12,168.0	2,099.31	5.755	1.975
eh_Hrvlfhffft	0	12.9	11.1	1.7	63.4	9.82	9.755	2.507
eh_Hrvlffftnu	0	86.2	89.8	59.2	96.9	9.02	0.834	-1.225
eh_Hrvhffft	0	424.1	184.1	8.6	3,564.3	657.04	10.453	3.056
eh_Hrvhffftnu	0	13.7	11.1	3.1	40.7	8.97	0.838	1.226

Table 5.5 Descriptive statistics (Disengagement indicators, n=80)

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
de_Sssq	0	3.7	3.6	2.3	5.0	0.69	-0.664	0.194
de_invitem2	0	3.6	4.0	1.0	6.0	1.36	-1.098	-0.404
de_invitem5	0	2.4	2.0	1.0	6.0	1.20	0.475	0.937
de_invitem11	0	2.2	2.0	1.0	5.0	1.03	-0.143	0.631
de_invitem12	0	1.9	2.0	1.0	4.0	0.91	0.099	0.884
de_invitem13	0	2.2	2.0	1.0	4.0	0.92	-0.591	0.429
de_invitem17	0	2.0	2.0	1.0	3.0	0.76	-1.262	0.042
de_invitem21	1	2.2	2.0	1.0	5.0	0.83	0.343	0.330
de_invitem22	0	2.1	2.0	1.0	4.0	0.89	-0.252	0.606

Table 5.6 Descriptive statistics (Performance indicators, n=80)

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
pf_Productivity	0	141.2	139.0	52.0	241.0	36.62	0.403	0.155
pf_Ergo60	0	24.9	20.4	0.1	59.8	17.93	-1.315	0.341
pf_ErgoRatio60	3	7.6	3.72	0.7	54.6	10.50	9.231	2.830

The PLS-SEM generally does not make any assumptions of data distribution, but Hair et al. (2017) recommended an analysis to check whether the data follow normal distributions. The results of normality tests, including the Kolmogorov-Smirnov test and the Shapiro-Wilk test, are summarized in Tables 5.7 through 5.11. When the null hypothesis “sample distribution is normal” was rejected, the corresponding variable was subjected to data transformation. When there were several applicable indicators for measuring the research construct, variables with normal distribution of data were selected and used for the PLS-SEM analysis. For example, as the parameter of a subject’s improper lifting technique, pf_Ergo60 and pf_ErgoRatio60 (in Table 5.11) are subjected to measuring the performance construct (specifically, safety performance) in the model. Instead of using the log-transformed value of the indicator, pf_Ergo60, the ratio scale of measurement (i.e., pf_ErgoRatio60) is preferentially used for model analysis because the ratio scale data is normally distributed.

Table 5.7 Tests of normality result (Task demands indicators)

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	*p* Values	Significance (p <0.05)?	Statistic	*p* Values	Significance (p <0.05)?
td_Hrbpm	0.074	[a]0.200	No	0.972	0.112	No
td_Enerkcal	0.070	[a] 0.200	No	0.973	0.122	No
td_Enermet	0.080	[a] 0.200	No	0.981	0.363	No
td_Wenerkcal	0.108	0.037	Yes	0.946	0.004	Yes
td_Wenermet	0.096	0.097	No	0.968	0.059	No
td_Rtlx	0.093	[a] 0.200	No	0.977	0.197	No
td_Physicald	0.095	0.180	No	0.964	0.036	Yes
td_Temporald	0.133	0.003	Yes	0.954	0.011	Yes
td_Mentald	0.176	0.000	Yes	0.855	0.000	Yes
td_Effort	0.093	[a] 0.200	No	0.974	0.133	No
td_Frustrationl	0.234	0.000	Yes	0.826	0.000	Yes
td_Inversedp	0.171	0.000	Yes	0.869	0.000	Yes
td_Rhr	0.122	0.009	Yes	0.933	0.001	Yes

Table 5.8 Tests of normality result (Personal resources indicators)

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	*p* Values	Significance (p <0.05)?	Statistic	*p* Values	Significance (p <0.05)?
pr_Resthr	0.073	[a] 0.200	No	0.988	0.722	No
pr_Smwt	0.072	[a] 0.200	No	0.983	0.440	No
pr_Hrr	0.113	0.024	Yes	0.933	0.001	Yes
pr_Sf12pcs	0.140	0.001	Yes	0.950	0.006	Yes
pr_Sf12mcs	0.181	0.000	Yes	0.880	0.000	Yes
pr_Sf12tot	0.165	0.000	Yes	0.896	0.000	Yes
pr_Pfnbs	0.501	0.000	Yes	0.439	0.000	Yes
pr_Rpnbs	0.340	0.000	Yes	0.755	0.000	Yes
pr_Bpnbs	0.405	0.000	Yes	0.568	0.000	Yes
pr_Ghnbs	0.322	0.000	Yes	0.789	0.000	Yes
pr_Sleepqual	0.108	0.037	Yes	0.968	0.065	No
pr_Totalsleep	0.117	0.017	Yes	0.893	0.000	Yes
pr_Sfi	0.100	0.070	No	0.959	0.020	Yes

Table 5.9 Tests of normality result (Personal exhaustion indicators)

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	*p* Values	Significance (p <0.05)?	Statistic	*p* Values	Significance (p <0.05)?
eh_Cis	0.082	[a] 0.200	No	0.988	0.735	No
eh_cisitem1	0.175	0.000	Yes	0.918	0.000	Yes
eh_cisitem2	0.185	0.000	Yes	0.916	0.000	Yes
eh_cisitem3	0.180	0.000	Yes	0.914	0.000	Yes
eh_cisitem4	0.316	0.000	Yes	0.794	0.000	Yes
eh_cisitem5	0.158	0.000	Yes	0.942	0.002	Yes
eh_cisitem6	0.281	0.000	Yes	0.762	0.000	Yes
eh_cisitem7	0.274	0.000	Yes	0.833	0.000	Yes
eh_cisitem8	0.191	0.000	Yes	0.884	0.000	Yes
eh_Sdnn	0.063	[a] 0.200	No	0.979	0.256	No
eh_Rmssd	0.082	[a] 0.200	No	0.962	0.028	Yes
eh_Hrvlffft	0.177	0.000	Yes	0.816	0.000	Yes
eh_Hrvlfhffft	0.098	0.081	No	0.879	0.000	Yes
eh_Hrvlffftnu	0.168	0.000	Yes	0.861	0.000	Yes
eh_Hrvhffft	0.320	0.000	Yes	0.544	0.000	Yes
eh_Hrvhffftnu	0.167	0.000	Yes	0.861	0.000	Yes

Table 5.10 Tests of normality result (Disengagement indicators)

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	*p* Values	Significance (p <0.05)?	Statistic	*p* Values	Significance (p <0.05)?
de_Sssq	0.107	0.038	Yes	0.973	0.124	No
de_invitem2	0.213	0.000	Yes	0.884	0.000	Yes
de_invitem5	0.256	0.000	Yes	0.862	0.000	Yes
de_invitem11	0.245	0.000	Yes	0.872	0.000	Yes
de_invitem12	0.248	0.000	Yes	0.808	0.000	Yes
de_invitem13	0.243	0.000	Yes	0.862	0.000	Yes
de_invitem17	0.208	0.000	Yes	0.808	0.000	Yes
de_invitem21	0.231	0.000	Yes	0.848	0.000	Yes
de_invitem22	0.271	0.000	Yes	0.848	0.000	Yes

Table 5.11 Tests of normality result (Performance indicators)

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	*p* Values	Significance (p <0.05)?	Statistic	*p* Values	Significance (p <0.05)?
pf_Productivity	0.059	[a] 0.200	No	0.988	0.719	No
pf_Ergo60	0.126	0.007	Yes	0.912	0.000	Yes
pf_ErgoRatio60	0.258	0.000	Yes	0.648	0.000	Yes

In the case when the data did not have any zero values, some of the variables were applied to the inverse transformation to make the variables consistent in to measure each corresponding construct in the research model positively. Each corresponding indicator is a measurement of its construct, positively (Figure 5.1). A decrease in the level of time domain heart rate variability (HRV), such as the eh_Sdnn (variable eh_Sdnn in **Appendix A**, Table A.3), is known to predict an increase in the level of a worker's exhaustion (Earnest et al., 2004). Thus, an increase in the level of eh_invSdnn variable (the inversed scale of eh_Sdnn, Figure 5.1) indicates an increased level of exhaustion. The original format of the Short Stress State Questionnaire (SSSQ) is designed to measure a respondent's engagement level on a given task. An increase in the level of de_invitem22 (inverse scale), as revealed in the SSSQ survey, indicates an increased level of disengagement. These variables were not used on the log-transformed scale because the normality of the data distribution was already met after the inverse transformation. The inverse transformation is one of the data transformation methods for normal distribution (Osborne, 2002).

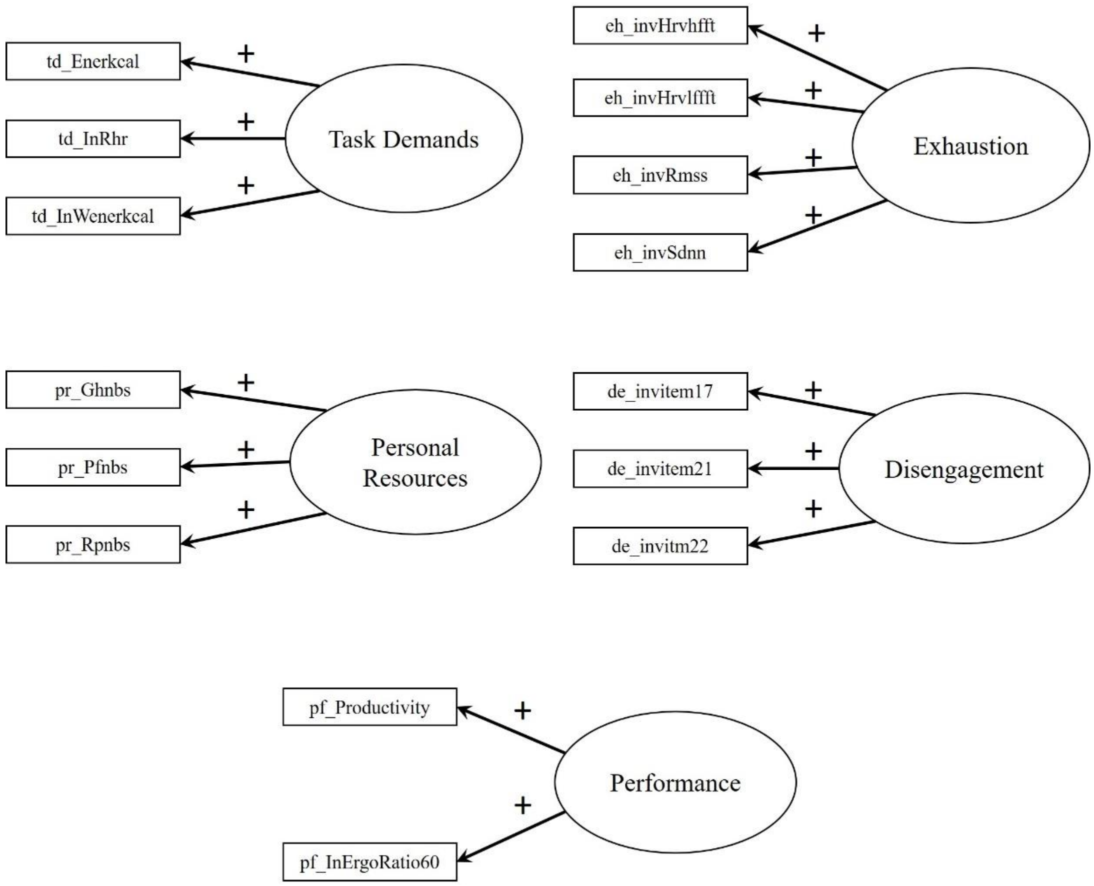

Figure 5.1 Examples of measurement models

In summary, concerning the rule of data transformation of the current research, the variables were log-transformed when the construct was measured in a positive direction (e.g., increased task demands construct indicates an increased heart rate measurement). If the construct was measured in a negative direction, then the normalization of the variables would have been satisfied through inverse values. Through the inverse transformation of the directional variables, all measurement variables ultimately predicted a construct in the positive direction. The descriptive statistics of the transformed variables are summarized in Table 5.12.

Table 5.12 Descriptive statistic log-transformed and inversed scale data

	Missing	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
Task Demands								
td_lnWenerkcal	1	4.973	5.075	4.152	5.888	0.438	-0.891	-0.153
td_lnWenermet	1	1.263	1.272	1.010	1.410	0.065	2.172	-0.804
td_lnRhr	0	3.516	3.575	2.719	4.376	0.384	-0.704	0.063
Personal Resources								
pr_invResthr	0	0.015	0.014	0.011	0.023	0.003	0.545	0.841
pr_lnHrr	2	2.555	2.723	-0.693	3.743	0.908	1.207	-1.064
pr_lnSf12pcs	0	4.019	4.032	3.754	4.200	0.088	0.996	-0.986
pr_lnSf12mcs	0	3.927	3.983	3.444	4.132	0.164	1.059	-1.372
pr_lnSf12tot	0	3.979	4.011	3.754	4.084	0.080	0.417	-1.122
pr_lnSleepQual	3	4.421	4.434	4.127	4.581	0.081	1.822	-1.003
pr_lnTotalsl	3	5.791	5.805	4.663	6.669	0.289	3.801	-0.719
pr_lnSfi	3	3.250	3.290	1.573	4.098	0.467	2.164	-0.983
pr_invSfi	3	0.044	0.037	0.017	0.207	0.029	15.054	3.455
Exhaustion								
eh_lnrmssd	0	2.922	3.053	1.639	3.886	0.571	-0.667	-0.494
eh_invSdnn	0	0.029	0.023	0.010	0.112	0.020	4.511	2.096
eh_invRmss	0	0.064	0.047	0.021	0.194	0.041	1.453	1.433
eh_invHrvlffft	0	0.002	0.001	0.000	0.021	0.003	26.449	4.587
eh_invHrvlfhffft	0	0.134	0.092	0.016	0.599	0.121	4.494	2.139
eh_invHrvlffftnu	0	0.012	0.011	0.010	0.017	0.001	2.626	1.711
eh_invHrvhffft	0	0.013	0.005	0.000	0.116	0.022	8.736	2.944
eh_invHrvhffftnu	0	0.106	0.098	0.025	0.328	0.064	1.293	1.100
Performance								
pf_lnErgo60	0	2.738	3.016	-2.303	4.091	1.305	5.001	-1.954
pf_lnErgoRatio60	3	1.349	1.313	-0.397	3.999	1.146	-0.819	0.388

As a result of an investigation of the patterns in survey responses, some of the subjects showed a straight lining pattern in their responses (i.e., extreme response style). For example, a subject answered all the items in the selected SSSQ in only one row, on a Likert scale from 1 to 5. This means that the respondent was more likely to have responded quickly without checking the details of each question. Therefore, the records of these responses were deleted from the dataset and processed as missing data. Through the analysis of a box plot of all the variables, data points that were detected as outliers were also deleted and processed as missing data. The mean value replacement was selected among the PLS-SEM analysis options for the processing of missing data in the SmartPLS 3.0 software. The missing value was less than 5% for each indicator (Tables 5.2 through 5.6); this shows the appropriateness of the mean value replacement method (Hair et al. 2017) for the current research. The missing data points were replaced by the average of the remaining values of each indicator while setting up the bootstrapping and running the PLS-SEM algorithm in the SmartPLS 3.0 software.

The bivariate Pearson correlations between the variables measured by the survey and sensors for the task demand construct, personal resources construct, and exhaustion construct are presented in Tables 5.13, 5.14, and 5.15, respectively. These tables essentially provide observations of the correlations between the survey and sensor measurements, which are designed to operationalize the research constructs. In the case of task demands indicators, it was difficult to find a significant correlation between survey measurements and sensor measurements. This tendency was also similar for indicators measuring personal resources (PR) and exhaustion (EX) constructs. Therefore, it was predicted that when the measurement model of each construct included the survey- and sensor-measured indicators, there would be potential issues in internal consistency reliability in the assessment of the measurement model.

Table 5.13 Pearson correlation coefficients for survey and sensor measurement variables of task demands construct

	td1	td2	td3	td4	td5	td6	td7	td8	td9	td10	td11	td12	td13	td14
td1	1.00													
td2	0.84[a]	1.00												
td3	0.75[a]	0.73[a]	1.00											
td4	0.77[a]	0.68[a]	0.50[a]	1.00										
td5	0.57[a]	0.62[a]	0.19	0.39[a]	1.00									
td6	0.75[a]	0.78[a]	0.79[a]	0.46[a]	0.26[b]	1.00								
td7	0.61[a]	0.61[a]	0.21	0.35[a]	0.49[a]	0.28[b]	1.00							
td8	-0.53[a]	0.01	-0.24[b]	-0.35[a]	-0.08	-0.17	-0.20	1.00						
td9	-0.10	-0.10	-0.07	0.05	-0.17	-0.09	-0.12	0.03	1.00					
td10	-0.11	-0.08	-0.08	0.09	-0.22[b]	-0.05	-0.12	0.08	0.92[a]	1.00				
td11	-0.15	0.06	-0.19	-0.01	-0.07	-0.03	0.11	0.35[a]	0.17	0.28[b]	1.00			
td12	-0.03	0.13	-0.08	0.04	-0.02	0.07	0.15	0.25[b]	0.20	0.25[b]	0.74[a]	1.00		
td13	-0.23[b]	-0.05	-0.22[b]	-0.05	-0.11	-0.12	-0.02	0.31[a]	0.21	0.30[a]	0.82[a]	0.32[a]	1.00	
td14	-0.04	0.04	0.01	0.10	-0.05	-0.01	-0.06	0.12	0.19	0.24[b]	0.08	0.10	0.25[b]	1.00

Note. td1: td_Percworkload; td2: td_Rtlx; td3: td_Physicald; td4: td_Temporald; td5: td_Mentald; td6: td_Effort; td7: td_Frustrationl; td8: td_Inversedp; td9: td_Rhr; td10: td_Hrbpm; td11: td_Enerkcal; td12: td_Enermet; td13: td_Wenerkcal; td14: td_Wenermet; a: Correlation is significant at the 0.01 level (2-tailed); b: Correlation is significant at the 0.05 level (2-tailed).

Table 5.14 Pearson correlation coefficients for survey and sensor measurement variables of personal resources construct

	pr1	pr2	pr3	pr4	pr5	pr6	pr7	pr8	pr9	pr10	pr11	pr12
pr1	1.00											
pr2	0.42[a]	1.00										
pr3	0.58[a]	0.56[a]	1.00									
pr4	0.63[a]	0.65[a]	0.48[a]	1.00								
pr5	0.62[a]	0.50[a]	0.20	0.34[a]	1.00							
pr6	0.60[a]	0.67[a]	0.48[a]	0.50[a]	0.25[b]	1.00						
pr7	0.02	0.24[b]	0.03	0.05	0.25[b]	0.12	1.00					
pr8	0.17	-0.25[b]	-0.10	0.08	-0.04	0.11	0.01	1.00				
pr9	-0.02	0.04	0.08	-0.14	0.01	0.02	0.09	-0.20	1.00			
pr10	-0.25[b]	-0.29[b]	-0.19	-0.20	-0.28[b]	-0.17	0.02	-0.09	0.11	1.00		
pr11	-0.05	-0.02	-0.11	0.01	-0.10	0.04	0.14	-0.02	0.24[b]	0.30[a]	1.00	
pr12	-0.23[b]	-0.23[b]	-0.07	-0.22	-0.22[b]	-0.16	-0.10	-0.03	-0.11	0.47[a]	0.01	1.00

Note. pr1: pr_Sf12pcs; pr2: pr_Sf12tot; pr3: pr_Pfnbs; pr4: pr_Rpnbs; pr5: pr_Bpnbs; pr6: pr_Ghnbs; pr7: pr_Resthr; pr8: pr_Smwt; pr9: pr_Hrr; pr10: pr_Sleepqual; pr11: pr_Totalsleep; pr12: pr_invSfi; a: Correlation is significant at the 0.01 level (2-tailed); b: Correlation is significant at the 0.05 level (2-tailed).

Table 5.15 Pearson correlation coefficients for survey and sensor measurement variables of exhaustion construct

	eh1	eh2	eh3	eh4	eh5	eh6	eh7	eh8	eh9	eh10	eh11	eh12	eh13	eh14	eh15	eh16
eh1	1.00															
eh2	0.68[a]	1.00														
eh3	0.73[a]	0.81[a]	1.00													
eh4	0.59[a]	0.16	0.24[b]	1.00												
eh5	0.68[a]	0.25[b]	0.31[a]	0.30[a]	1.00											
eh6	0.29[b]	0.15	-0.05	0.16	-0.01	1.00										
eh7	0.46[a]	-0.03	0.12	0.22[b]	0.57[a]	-0.07	1.00									
eh8	0.61[a]	0.22[b]	0.37[a]	0.27[b]	0.54[a]	-0.09	0.34[a]	1.00								
eh9	0.70[a]	0.24[b]	0.36[a]	0.39[a]	0.54[a]	0.01	0.50[a]	0.55[a]	1.00							
eh10	-0.27[b]	-0.22[b]	-0.20	-0.10	-0.28[b]	-0.12	-0.08	-0.13	-0.13	1.00						
eh11	-0.20	-0.23[b]	-0.16	-0.07	-0.17	-0.18	0.01	-0.05	0.00	0.90[a]	1.00					
eh12	-0.27[b]	-0.23[b]	-0.22[b]	-0.05	-0.24[b]	-0.14	-0.05	-0.11	-0.15	0.88[a]	0.74[a]	1.00				
eh13	0.03	0.08	0.09	0.21	-0.19	0.12	-0.10	-0.10	-0.14	-0.04	-0.31[a]	0.04	1.00			
eh14	0.07	0.09	0.07	0.06	-0.03	0.17	-0.06	-0.04	-0.03	-0.22	-0.51[a]	-0.16	0.67[a]	1.00		
eh15	-0.16	-0.17	-0.15	0.06	-0.15	-0.09	-0.03	-0.10	-0.07	0.66[a]	0.69[a]	0.74[a]	-0.32[a]	-0.60[a]	1.00	
eh16	-0.07	-0.09	-0.07	-0.06	0.03	-0.17	0.06	0.04	0.03	0.22	0.51[a]	0.17	-0.67[a]	-1.00[a]	0.60[a]	1.00

Note. eh1: eh_Cis; eh2: eh_cisitem1; eh3: eh_cisitem2; eh4: eh_cisitem3: eh5: eh_cisitem4; eh6: eh_cisitem5; eh7: eh_cisitem6; eh8: eh_cisitem7; eh9: eh_cisitem8; eh10: eh_Sdnn; eh11: eh_Rmssd; eh12: eh_Hrvlffft; eh13: eh_Hrvlfhffft; eh14: eh_Hrvlffftnu; eh15: eh_Hrvhffft; eh16: eh_Hrvhffftnu; a: Correlation is significant at the 0.01 level (2-tailed); b: Correlation is significant at the 0.05 level (2-tailed).

5.2 Evaluations of Measurement and Structural Models

According to existing studies (e.g., Barriera-Viruet, Sobeih, Daraiseh, & Salem, 2006; Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001), there is a potential inconsistency between self-reporting, observation, and direct measurement methods that measure human factors, owing to a measurement error related to various exposure metrics. In the preliminary data analysis, conducted as part of the current research, all surveys (i.e., self-reporting) and sensor (i.e., direct measurement) measurements did not correspond to one another when measuring research constructs in the same direction. Therefore, the evaluation of measurement and structural models was conducted by separating survey and sensor measurements. In the current research, the first step of data analysis was conducted using separate models as follows: (1) —a survey model and (2) a sensor model. Subsequently, the survey and sensor measurements that met the reliability and validity criteria for the measurement model were selected for a relevant construct. Next, the model in which the survey and sensor indicators were mixed was analyzed as the final (3) combined model.

5.2.1 Survey Model

Measurement model: The model that included only survey indicators that measure each construct was analyzed. As the first step, a PLS-SEM analysis was performed by including all measurement variables in the model simultaneously (i.e., simultaneous entry method). A confirmation on internal consistency, convergent validity, and discriminant validity led to the removal of measurement indicators that could lower model prediction accuracy. The productivity indicator (i.e., pf_Productivity) and safety indicator (i.e., pf_InErgoRatio60) were set up to measure one performance construct and subsequently to evaluate the measurement model.

The measurement model did not meet the evaluation criteria, as shown in Tables 5.16 and 5.17. In terms of internal consistency reliability, which should be higher than 0.7, there are constructs, including TD and PF, which do not meet this requirement. In the initial measurement model, including all survey measurement variables, Cronbach’s α values were significantly lower than 0.7 in the TD and PF constructs. The average variance extracted (AVE), which is an indicator of the convergent validity, must be 0.5 or more; however, TD, EX, and PF did not satisfy this requirement.

Table 5.16 Reliability and convergent validity (Survey model: step1)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.589	0.719	0.442
PR	0.704	0.816	0.533
EX	0.741	0.814	0.391
DE	0.864	0.887	0.503
PF	0.533	0.474	0.450

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PF: Performance.

Outer loadings of many indicators were not greater than 0.7 (Table 5.17). For the indicator reliability, outer loadings less than 0.4 needed to be removed (Hair et al., 2017). Indicators between 0.4 and 0.7 were removed if the AVE increased due to the elimination of the indicators.

Table 5.17 Analysis of cross-loadings of the latent variables (Survey model: step1)

Measured variables	Correlations with respect to the latent variables				
	TD	PR	EX	DE	PF
td_Effort	0.679	-0.042	0.327	0.040	0.032
td_Frustrationl	0.665	-0.263	0.424	0.139	-0.059
td_Inversedp	-0.517	0.296	-0.410	-0.392	-0.289
td_Mentald	0.655	-0.279	0.472	0.264	-0.079
td_Physicald	0.660	0.050	0.268	0.086	0.148
td_Temporald	**0.786**	-0.115	0.486	0.125	0.138
pr_Bpnbs	-0.181	0.519	-0.266	-0.159	0.041
pr_Ghnbs	-0.260	**0.844**	-0.523	-0.370	-0.090
pr_Pfnbs	-0.110	**0.740**	-0.350	-0.236	0.060
pr_Rpnbs	-0.207	**0.776**	-0.374	-0.171	0.083
eh_cisitem1	0.520	0.002	0.484	0.133	0.077
eh_cisitem2	0.541	-0.163	0.626	0.200	0.169
eh_cisitem3	0.307	-0.214	0.561	0.539	0.106
eh_cisitem4	0.446	-0.330	**0.770**	0.343	0.054
eh_cisitem5	0.019	0.176	0.002	0.063	0.048
eh_cisitem6	0.356	-0.479	0.621	0.287	0.000
eh_cisitem7	0.340	-0.519	**0.737**	0.386	0.062
eh_cisitem8	0.482	-0.596	**0.816**	0.464	-0.005
de_invitem11	0.140	0.044	0.322	**0.764**	0.176
de_invitem12	0.002	-0.127	0.297	**0.726**	0.081
de_invitem13	0.175	-0.119	0.377	**0.768**	0.149
de_invitem17	0.356	-0.456	0.553	**0.747**	0.285
de_invitem2	0.038	0.119	0.052	0.420	0.043
de_invitem21	0.246	-0.366	0.429	**0.851**	0.213
de_invitem22	0.277	-0.326	0.322	0.662	0.249
de_invitem5	0.065	-0.220	0.295	0.652	0.069
pf_Productivity	-0.096	0.267	-0.092	-0.085	0.047
pf_lnErgoRatio60	0.072	0.095	0.052	0.213	**0.948**

Note. Bold texts: the indicators' outer-loadings are greater than 0.7; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PF: Performance.

When the productivity and safety indicators (i.e., pf_Productivity and pf_lnErgoRatio60), which measure performance construct, were grouped into one construct (i.e., performance construct), the pf_Productivity indicator showed a very low outer loading (i.e., 0.047); this penalized the indicator reliability and composite reliability in Table 5.16. Thus, the performance construct was divided into two different constructs—productivity performance construct and safety performance construct. Thus, the productivity performance construct was measured by the indicator pf_Productivity and the safety performance construct was measured by the indicator pf_lnErgoRatio60. Subsequently, how this change influenced the evaluation criteria of the measurement model was investigated. The results of the assessment of the revised measurement model are summarized in Tables 5.18 and 5.19; it presents the fact that there are still issues concerning internal consistency, convergent validity, and cross-loading values in the measurement model. The Cronbach's α for TD was less than 0.7, AVE for EX was lower than 0.5, and outer loads for many indicators were less than 0.7.

Table 5.18 Reliability and convergent validity (Survey model: step2)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.589	0.719	0.442
PR	0.704	0.816	0.533
EX	0.741	0.813	0.391
DE	0.864	0.887	0.502
PPD	[a]1.000	[a]1.000	[a]1.000
PES	[a]1.000	[a]1.000	[a]1.000

Note. a: Single item construct; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.19 Analysis of cross-loadings of the latent variables (Survey model: step2)

Measured variables	Correlations with respect to the latent variables					
	TD	PR	EX	DE	PPD	PES
td_Effort	0.678	-0.042	0.324	0.039	-0.157	-0.020
td_Frustrationl	0.665	-0.263	0.424	0.140	0.101	-0.023
td_Inversedp	-0.518	0.296	-0.411	-0.393	0.179	-0.213
td_Mentald	0.655	-0.279	0.471	0.264	-0.058	-0.092
td_Physicald	0.659	0.051	0.266	0.086	-0.121	0.100
td_Temporald	**0.786**	-0.115	0.486	0.126	-0.021	0.122
pr_Bpnbs	-0.181	0.519	-0.267	-0.160	0.100	0.070
pr_Ghnbs	-0.260	**0.843**	-0.525	-0.373	0.272	0.003
pr_Pfnbs	-0.110	**0.740**	-0.352	-0.238	0.165	0.109
pr_Rpnbs	-0.207	**0.777**	-0.378	-0.174	0.197	0.140
eh_cisitem1	0.520	0.003	0.481	0.133	-0.049	0.056
eh_cisitem2	0.541	-0.163	0.625	0.201	-0.087	0.130
eh_cisitem3	0.307	-0.214	0.554	0.539	0.134	0.142
eh_cisitem4	0.446	-0.330	**0.772**	0.344	-0.089	0.022
eh_cisitem5	0.019	0.176	-0.005	0.062	0.124	0.084
eh_cisitem6	0.357	-0.479	0.623	0.289	-0.085	-0.027
eh_cisitem7	0.341	-0.519	**0.740**	0.387	-0.221	-0.013
eh_cisitem8	0.483	-0.596	**0.817**	0.465	-0.028	-0.014
de_invitem11	0.140	0.044	0.319	**0.761**	0.119	0.202
de_invitem12	0.002	-0.127	0.295	**0.723**	0.089	0.104
de_invitem13	0.174	-0.119	0.374	**0.766**	0.075	0.163
de_invitem17	0.357	-0.456	0.554	**0.750**	-0.200	0.202
de_invitem2	0.038	0.119	0.051	0.417	-0.009	0.037
de_invitem21	0.246	-0.366	0.427	**0.852**	-0.198	0.136
de_invitem22	0.277	-0.326	0.321	0.662	-0.083	0.206
de_invitem5	0.065	-0.220	0.292	0.652	-0.057	0.047
pf_Productivity	-0.096	0.267	-0.095	-0.087	[a] **1.000**	0.363
pf_lnErgoRatio60	0.072	0.095	0.051	0.212	0.363	[a] **1.000**

Note. a: Single item construct; Bold texts: the indicators' outer-loadings are greater than 0.7; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

To address the issues previously found in Tables 5.18 and 5.19, the variables with cross-loadings below 0.7 were removed from the analysis, but the variables that presented cross-loadings very close to 0.7 (e.g., 0.68 and 0.69) were included in the analysis. As suggested by Hair et al. (2017), indicators were retained if the removal of the indicator with an outer loading between 0.40 and 0.70 did not lead to an increase in AVE (i.e., composite reliability). Therefore, the measurement variables td_Effort, td_Physicald, and de_invitem12 were maintained in the measurement model. Subsequently, the reliability and convergent validity were reassessed and the results were summarized in Table 5.20.

Table 5.20 Reliability and convergent validity (Survey model: step3)

Constructs	Cronbach's Alpha	Composite Reliability	AVE
TD	0.752	0.813	0.523
PR	0.738	0.849	0.653
EX	0.805	0.872	0.630
DE	0.855	0.886	0.566
PPD	[a]1.000	[a]1.000	[a]1.000
PES	[a]1.000	[a]1.000	[a]1.000

Note. a: Single item construct; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

As depicted in Table 5.21, most factor loadings were greater than 0.7, and the factor loadings of td_Effort, td_Physicald, and de_invitem12 were above 0.65. Thus, the measurement items met the acceptable level of indicator reliability.

Table 5.21 Analysis of cross-loadings of the latent variables (Survey model: step3)

Measured variables	Correlations with respect to the latent variables					
	TD	PR	EX	DE	PPD	PES
td_Effort	**0.663**	-0.043	0.154	0.048	-0.157	-0.020
td_Frustrationl	**0.752**	-0.266	0.398	0.158	0.101	-0.023
td_Physicald	**0.631**	0.070	0.096	0.092	-0.121	0.100
td_Temporald	**0.831**	-0.109	0.411	0.178	-0.021	0.122
pr_Ghnbs	-0.191	**0.856**	-0.562	-0.396	0.272	0.003
pr_Pfnbs	-0.105	**0.767**	-0.395	-0.252	0.165	0.109
pr_Rpnbs	-0.145	**0.799**	-0.502	-0.195	0.197	0.140
eh_cisitem4	0.399	-0.351	**0.814**	0.355	-0.089	0.022
eh_cisitem6	0.292	-0.477	**0.735**	0.294	-0.085	-0.027
eh_cisitem7	0.280	-0.492	**0.776**	0.413	-0.221	-0.013
eh_cisitem8	0.439	-0.587	**0.846**	0.494	-0.028	-0.014
de_invitem11	0.056	0.047	0.267	**0.739**	0.119	0.202
de_invitem12	-0.117	-0.128	0.246	**0.673**	0.089	0.104
de_invitem13	0.066	-0.099	0.267	**0.720**	0.075	0.163
de_invitem17	0.291	-0.461	0.557	**0.797**	-0.200	0.202
de_invitem21	0.145	-0.355	0.425	**0.883**	-0.198	0.136
de_invitem22	0.187	-0.315	0.297	**0.680**	-0.083	0.206
pf_Productivity	-0.005	0.269	-0.130	-0.103	[a]**1.000**	0.363
pf_lnErgoRatio60	0.059	0.093	-0.011	0.226	0.363	[a]**1.000**

Note. a: Single item construct; Bold texts: the indicators' outer-loadings are greater than 0.7 (and close to 0.7); TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

With the revised measurement model (of the survey model), the discriminant validity was acceptable because the square root of the AVE of each reflective construct was greater than its greatest correlation between other constructs (Table 5.22), according to the Fornell-Larcker criterion (Fornell & Larcker, 1981). Thus, the specific construct was more correlated with its measurement variables than it was with other constructs.

Table 5.22 Comparisons of correlation between constructs and squared root of AVE for discriminant validity (Survey model: step3)

	TD	PR	EX	DE	PPD	PES
TD	**0.723**					
PR	-0.188	**0.808**				
EX	0.449	-0.611	**0.794**			
DE	0.189	-0.360	0.501	**0.752**		
PPD	-0.005	0.269	-0.130	-0.103	[a]**1.000**	
PES	0.059	0.093	-0.011	0.226	0.363	[a]**1.000**

Note. Bold diagonal values: The square root of average variance extracted; a: Single item construction; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The Heterotrait–monotrait ratio of correlation (HTMT) was introduced by Henseler et al. (2015), and it is a criterion that is used to assess discriminant validity. The confidence interval of HTMT from the bootstrapping result should not include 1 to achieve acceptable discriminant validity (Hair et al., 2017). Further, based on the suggestion by Kline (2015), all HTMT values should be lower than 0.85 in the final revised measurement model (of the survey model). Table 5.23 shows that the conditions for the discriminant validity of the measurement model were satisfied.

Table 5.23 Heterotrait–monotrait ratio of correlation (Survey model: step3)

	Original Sample	Sample Mean	Bias	95% Confidence Intervals	
				2.50%	97.50%
TD → DE	0.236	0.305	0.069	0.194	0.454
TD → EX	0.447	0.480	0.033	0.295	0.691
TD → PPD	0.152	0.206	0.054	0.069	0.390
TD → PES	0.100	0.168	0.068	0.063	0.339
TD → PR	0.263	0.310	0.047	0.192	0.464
PR → DE	0.381	0.427	0.046	0.278	0.623
PR → EX	0.767	0.777	0.010	0.606	0.952
PR → PPD	0.304	0.310	0.006	0.132	0.495
PR → PES	0.120	0.184	0.064	0.043	0.424
EX → DE	0.532	0.535	0.003	0.348	0.726
PPD → DE	0.181	0.206	0.025	0.094	0.338
PPD → EX	0.149	0.211	0.062	0.069	0.420
PES → DE	0.239	0.246	0.007	0.081	0.454
PES → EX	0.027	0.127	0.100	0.040	0.281
PES → PPD	0.363	0.358	-0.005	0.168	0.520

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Since the final measurement model with selected survey indicators satisfied the internal consistency, convergent validity, and discriminant validity of the measurement model, assessment of the structural model was conducted as the second step in the two-step process of model evaluation.

<u>Structural model:</u> The PLS-SEM analysis used the bootstrapping procedure to estimate the size and significance of the path coefficient. In the SmartPLS 3.0 program, the number of bootstrap samples was set to 5000, as the recommended minimum number of bootstrap samples (Hair et al.,2017). As a result of bootstrapping, Table 5.24 summarizes the coefficient of determination (R^2) for all endogenous constructs as one of the criteria for assessing the structural model. R^2 for endogenous constructs should be greater than 10%, as a rule of thumb, as suggested by Falk and

Miller (1992). The R^2 for EX and DE constructs were acceptable. However, the R^2 values for PPD and PES were low.

Table 5.24 Coefficient of determination (Survey model: step3)

Constructs	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
EX	0.489	0.521	0.076	6.451	0.000
DE	0.255	0.286	0.081	3.160	0.002
PPD	0.019	0.052	0.048	0.392	0.695
PES	0.072	0.092	0.053	1.347	0.178

Note. EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The criteria for identifying effect size f^2 are 0.02, 0.15, and 0.35, indicating small, medium, and large effects of the corresponding constructs (Cohen, 1988). In the structural model, the effect sizes of PR on DE, EX on PPD, and DE on PPD were small, based on the guideline, as shown in Table 5.25.

Table 5.25 Result of f^2 effect size (Survey model: step3)

	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
TD → EX	0.226	0.292	0.158	1.428	0.153
PR → EX	0.562	0.614	0.196	2.867	0.004
PR → DE	0.006	0.030	0.048	0.128	0.898
EX → DE	0.169	0.190	0.099	1.705	0.088
EX → PPD	0.008	0.026	0.035	0.240	0.810
EX → PES	0.022	0.035	0.037	0.602	0.547
DE → PPD	0.002	0.019	0.032	0.060	0.952
DE → PES	0.077	0.091	0.065	1.189	0.235

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The standard error of the coefficient was also calculated through the bootstrapping method. The t-value was calculated through the process. If the calculated t-value exceeds the reference t-value at the selected level, then the coefficient would be significantly different from zero (Hair et al., 2017). According to Hair et al. (2017), the critical t-values of the two-sided test were 1.65, 1.96, and 2.57 for significance levels 1%, 5%, and 10%, respectively. The results of the estimated path coefficients (β), t-value, p-value, and confidence intervals are summarized in Table 5.26.

Table 5.26 Significance testing results of the structural model path coefficient (Survey model: step3)

	Path Coefficients	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p <0.05)?
				2.50%	97.50%	
TD → EX	0.346	4.057	0.000	0.137	0.479	Yes
PR → EX	-0.546	9.372	0.000	-0.659	-0.430	Yes
PR → DE	-0.086	0.555	0.579	-0.369	0.243	No
EX → DE	0.448	3.884	0.000	0.187	0.644	Yes
EX → PPD	-0.104	0.693	0.488	-0.389	0.207	No
EX → PES	-0.166	1.429	0.153	-0.382	0.083	No
DE → PPD	-0.050	0.345	0.730	-0.322	0.246	No
DE→ PES	0.309	2.782	0.005	0.065	0.500	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance

The PLS-SEM analysis can determine the magnitude of the direct and indirect effects of latent variables included in a model. A direct effect refers to a variable's direct effect on another variable, while an indirect effect is the effect between two variables being mediated by another variable (Hair et al., 2017). The total effect is the sum of the direct and indirect effects of one variable on the other.

In Table 5.27, a significance testing of the total effects was conducted without considering the mediating effect of the EX and DE (see 5.4 Mediation effect), and thus direct relationships between TD and PPD, TD and PES, PR and PPD, and PR and PES were not significant in the survey model.

The mediating effect of the EX and DE on the relationship between the lowest-order components (i.e., TD and PR) and highest-order components (i.e., PES and PPD) is discussed in the latter section of this chapter (5.2.6. Mediating effect).

Table 5.27 Significance testing results of the total effects (Survey model: step3)

	Total effects	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.346	4.057	0.000	0.137	0.479	Yes
TD → DE	0.155	2.968	0.003	0.053	0.253	Yes
TD → PPD	-0.044	0.815	0.415	-0.156	0.061	No
TD → PES	-0.009	0.220	0.826	-0.095	0.078	No
PR → EX	-0.546	9.372	0.000	-0.659	-0.430	Yes
PR → DE	-0.330	2.728	0.006	-0.504	0.031	Yes
PR → PPD	0.074	0.930	0.352	-0.099	0.213	No
PR → PES	-0.012	0.174	0.862	-0.145	0.118	No
EX → DE	0.448	3.884	0.000	0.187	0.644	Yes
EX → PPD	-0.127	0.890	0.373	-0.392	0.163	No
EX → PES	-0.027	0.235	0.814	-0.257	0.199	No
DE → PPD	-0.050	0.345	0.730	-0.322	0.246	No
DE → PES	0.309	2.782	0.005	0.065	0.500	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Based on the results summarized in Figure 5.2 and Table 5.28, the higher the TD, the higher will be the level of EX (β = 0.346; t = 4.057; p < 0.001); hence, *Hypothesis 1*, higher levels of task demands are associated with higher levels of exhaustion, was supported. Further, as hypothesized, *Hypothesis 2* was supported based to the finding that the higher the PR, the lower will be the level of EX (β = -0.546; t = 9.372; p < 0.001). However, the effect of PR on DE was not significant (β = -0.086; t = 0.555; p = 0.579); thus, *Hypothesis 3* was not supported. The result that DE increases (β = 0.448; t = 3.884; p < 0.001) with an increase in EX supports *Hypothesis 4*. The effects of EX on PPD and PES with coefficients of -0.104 and -0.166, respectively, were not significant (p =

0.488 and p = 0.153). Thus, both *Hypothesis 5*a* and *Hypothesis 5*b* were not supported. The effect of DE on PPD was not significant (β = -0.050; t = 0.345; p = 0.730); hence, *Hypothesis 6*a* was not supported. The higher the DE, the higher will be the PES (β = 0.309; t = 2.782; p <0.05); this finding supported *Hypothesis 6*b*. However, there was a reverse direction of association between DE and PES constructs, unlike what this research hypothesized.

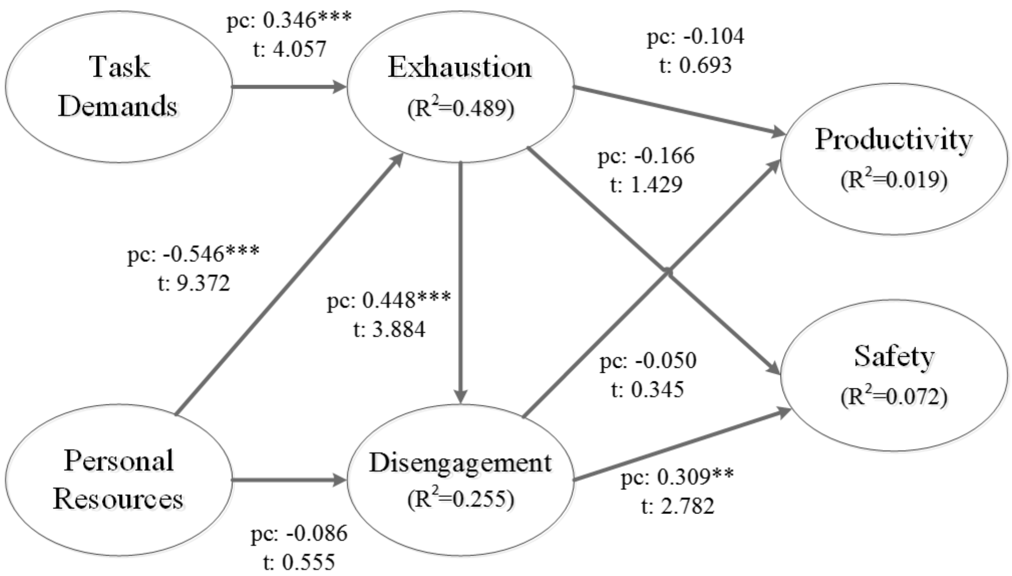

Figure 5.2 Path diagram for the model with survey measurements (pc: Path coefficient; t: t statistic; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

Table 5.28 Hypothesis testing results in the survey model (Survey model: step3)

Hypotheses	Constructs and direction of relationships	Standardized path coefficient (β)	*t*-Value	*p*-Value	Inference
H1	TD→EX (+)	0.346	4.057	0.000	Supported
H2	PR→EX (-)	-0.546	9.372	0.000	Supported
H3	PR→DE (-)	-0.086	0.555	0.579	Not supported
H4	EX→DE (+)	0.448	3.884	0.000	Supported
H5*a	EX→PPD (-)	-0.104	0.693	0.488	Not supported
H5*b	EX→PES (-)	-0.166	1.429	0.153	Not supported
H6*a	DE→PPD (-)	-0.050	0.345	0.730	Not supported
H6*b	DE→PES (-)	0.309	2.782	0.005	Supported (Reverse)

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

5.2.2 Sensor Model

Measurement model: The first step involved in evaluating the sensor measurement model was to set up a productivity indicator (i.e., pf_Productivity) and safety indicator (i.e., pf_InErgoRatio60) to measure a single performance construct. All sensor indicators that measure each of the constructs were added to the model and evaluated for the measurement model. However, as previously addressed, data collection to measure the disengagement construct using the EEG sensor could not be implemented in this research. Therefore, the eight items of the SSSQ survey were included in the sensor model as measurement variables of the disengagement construct in the sensor model. All the sensor measurements estimated from the data collected through the heart rate monitor and activity/sleep tracker were included in the model. Cronbach's α values were significantly lower than 0.7 in PR, EX, and PF constructs. The results of the convergent validity assessment in Table 5.29 indicate that CR values for PR and PF do not meet the threshold, 0.7. Further, except for the EX construct, the threshold of AVE (i.e., 0.5) was not satisfied for other constructs' AVE values.

Table 5.29 Reliability and convergent validity (Sensor model: step1)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.746	0.823	0.449
PR	0.263	0.405	0.224
EX	0.579	0.771	0.523
DE	0.864	0.819	0.387
PF	0.533	0.551	0.486

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PF: Performance.

Table 5.30 Analysis of cross-loadings of the latent variables (Sensor model: step1)

Measured variables	Correlations with respect to the latent variables				
	TD	PR	EX	DE	PF
td_Enerkcal	**0.696**	0.135	0.243	-0.414	0.392
td_Enermet	0.598	0.124	0.290	-0.396	0.538
td_Hrbpm	**0.840**	0.229	0.443	-0.131	0.199
td_lnRhr	**0.772**	0.070	0.395	-0.066	0.215
td_lnWenerkcal	0.644	0.080	0.254	-0.322	0.224
td_lnWenermet	0.367	0.211	0.213	-0.242	0.400
pr_Smwt	0.029	0.438	0.299	-0.077	0.335
pr_invResthr	-0.323	-0.476	-0.261	0.054	-0.041
pr_invSfi	-0.141	0.349	0.059	0.108	-0.057
pr_lnHrr	0.228	0.296	0.096	0.059	0.000
pr_lnSleepQual	0.023	**0.705**	0.212	0.277	0.006
pr_lnTotalsl	0.124	0.467	0.047	0.135	0.101
eh_invHrvhffft	0.415	0.365	**0.949**	0.053	0.371
eh_invHrvhffftnu	-0.126	0.173	0.189	0.068	0.118
eh_invHrvlffft	0.451	0.313	**0.891**	0.130	0.334
eh_invHrvlffftnu	0.226	-0.266	-0.290	-0.118	-0.152
eh_invHrvlfhffft	0.200	-0.162	-0.272	-0.098	-0.150
eh_invRmss	0.493	0.428	**0.919**	-0.029	0.340
eh_invSdnn	0.520	0.379	**0.965**	0.068	0.377
de_invitem11	-0.165	0.101	0.107	0.509	0.078
de_invitem12	-0.207	0.073	0.015	0.427	0.070
de_invitem13	-0.276	0.055	0.056	0.518	0.041
de_invitem17	-0.226	0.141	0.097	**0.872**	-0.260
de_invitem2	-0.411	-0.040	-0.073	0.290	-0.019
de_invitem21	-0.283	0.165	0.060	**0.907**	-0.242
de_invitem22	-0.337	-0.047	-0.073	**0.680**	-0.137
de_invitem5	-0.402	0.085	0.036	0.509	-0.072
pf_Productivity	0.422	0.161	0.368	-0.224	**0.975**
pf_lnErgoRatio60	-0.006	-0.075	0.022	0.188	0.147

Note. Bold texts: the indicators' outer-loadings are greater than 0.7 (and close to 0.7); TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PF: Performance.

The indicator reliability was not acceptable when the productivity and safety indicators were set as indicators to measure a single performance construct because the cross-loading for pf_lnErgoRatio60 was smaller than 0.4 (Table 5.31). Therefore, the productivity and safety performances were defined by separate constructs, which were measured by pf_Productivity and pf_lnErgoRatio60, respectively. Subsequently, the revised measurement model was assessed and its results were summarized in Tables 5.31 and 5.32.

Table 5.31 Reliability and convergent validity (Sensor model: step2)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.746	0.823	0.449
PR	0.263	0.331	0.211
EX	0.579	0.770	0.525
DE	0.864	0.881	0.490
PPD	[a]1.000	[a]1.000	[a]1.000
PES	[a]1.000	[a]1.000	[a]1.000

Note. a: Single item construct; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.32 Analysis of cross-loadings of the latent variables (Sensor model: step2)

	Correlations with respect to the latent variables					
Measured variables	TD	PR	EX	DE	PPD	PES
td_Enerkcal	**0.700**	0.161	0.243	-0.431	0.333	-0.160
td_Enermet	0.600	0.130	0.289	-0.387	0.493	-0.063
td_Hrbpm	**0.837**	0.237	0.436	-0.137	0.189	0.011
td_lnRhr	**0.769**	0.054	0.389	-0.092	0.226	0.106
td_lnWenerkcal	0.647	0.124	0.256	-0.307	0.191	-0.090
td_lnWenermet	0.368	0.244	0.212	-0.213	0.404	0.120
pr_Smwt	0.030	0.524	0.303	-0.039	0.348	0.146
pr_invResthr	-0.324	-0.547	-0.260	-0.006	0.005	0.194
pr_invSfi	-0.142	0.272	0.059	0.039	-0.062	-0.035
pr_lnHrr	0.227	0.243	0.096	0.000	-0.020	-0.088
pr_lnSleepQual	0.022	0.610	0.212	0.205	-0.008	-0.060
pr_lnTotalsl	0.125	0.430	0.047	0.126	0.089	-0.030
eh_invHrvhffft	0.415	0.378	**0.949**	0.037	0.357	0.030
eh_invHrvhffftnu	-0.124	0.193	0.201	0.086	0.122	0.049
eh_invHrvlffft	0.451	0.327	**0.889**	0.112	0.340	0.113
eh_invHrvlffftnu	0.223	-0.284	-0.301	-0.121	-0.134	0.040
eh_invHrvlfhffft	0.198	-0.187	-0.282	-0.105	-0.131	0.049
eh_invRmss	0.492	0.452	**0.920**	-0.001	0.302	-0.081
eh_invSdnn	0.519	0.398	**0.962**	0.081	0.363	0.035
de_invitem11	-0.166	0.119	0.108	**0.762**	0.119	0.202
de_invitem12	-0.208	0.071	0.015	**0.690**	0.089	0.104
de_invitem13	-0.277	0.059	0.057	**0.737**	0.075	0.163
de_invitem17	-0.227	0.115	0.098	**0.777**	-0.200	0.202
de_invitem2	-0.413	-0.061	-0.073	0.384	-0.009	0.037
de_invitem21	-0.285	0.139	0.062	**0.875**	-0.198	0.136
de_invitem22	-0.338	-0.067	-0.072	0.666	-0.083	0.206
de_invitem5	-0.403	0.057	0.038	0.599	-0.057	0.047
pf_Productivity	0.422	0.187	0.369	-0.096	[a]**1.000**	0.363
pf_lnErgoRatio60	-0.007	-0.069	0.023	0.220	0.363	[a]**1.000**

Note. a: Single item construct; Bold texts: the indicators' outer-loadings are greater than 0.7 (and close to 0.7); TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The result in Table 5.33 shows that the internal consistency reliability assessed by Cronbach's α and the composite reliability of several constructs did not exceed the lower bound (i.e., 0.70) of their acceptable threshold values. Further, the cross-loadings of many indicators in Table 5.33 did not exceed the recommended threshold value, 0.70. Thus, additional reiterative procedures to remove indicators penalizing the internal consistency and convergent validity were performed. The indicators were removed if the removal of the indicator with a cross-loading between 0.40 and 0.70 led to an increase in AVE (i.e., convergent reliability), based on the suggestion by Hair et al. (2017).

Table 5.33 Reliability and convergent validity (Sensor model: step3)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.674	0.803	0.577
PR	0.354	0.753	0.606
EX	0.951	0.965	0.873
DE	0.792	0.872	0.696
PPD	[a]1.000	[a]1.000	[a]1.000
PES	[a]1.000	[a]1.000	[a]1.000

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

After the reiterative procedures, the measurement items satisfied the acceptable level of indicator reliability. As depicted in Table 5.34, all cross-loadings, except for the item de_invitem22, were greater than 0.7 in the final measurement model (of the sensor model). The factor loading of the item de_invitem22 was very close to the acceptable threshold, 0.7, and its removal did not lead to an increase in AVE, and hence the item was retained in the model.

Table 5.34 Analysis of cross-loadings of the latent variables (Sensor model: step3)

Measured variables	Correlations with respect to the latent variables					
	TD	PR	EX	DE	PPD	PED
td_Enerkcal	**0.745**	0.168	0.239	-0.384	0.333	-0.160
td_lnRhr	**0.757**	0.185	0.430	-0.045	0.226	0.106
td_lnWenerkcal	**0.776**	0.047	0.245	-0.286	0.191	-0.090
pr_lnHrr	0.228	**0.716**	0.094	0.061	-0.020	-0.088
pr_lnTotalsl	0.085	**0.836**	0.041	0.129	0.089	-0.030
eh_invHrvhffft	0.357	0.030	**0.944**	0.037	0.357	0.030
eh_invHrvlffft	0.375	0.028	**0.912**	0.124	0.340	0.113
eh_invRmss	0.435	0.131	**0.904**	-0.030	0.302	-0.081
eh_invSdnn	0.455	0.113	**0.975**	0.072	0.363	0.035
[b] de_invitem17	-0.192	0.152	0.098	**0.881**	-0.200	0.202
[b] de_invitem21	-0.218	0.154	0.053	**0.908**	-0.198	0.136
[b] de_invitem22	-0.310	-0.085	-0.081	**0.698**	-0.083	0.206
pf_Productivity	0.323	0.052	0.365	-0.207	[a]**1.000**	0.363
pf_lnErgoRatio60	-0.021	-0.071	0.026	0.207	0.363	[a]**1.000**

Note. a: Single item construct; b: survey measurements used (no indicators measured by sensor for the disengagement construct); Bold texts: the indicators' outer-loadings are greater than 0.7 (and close to 0.7); TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

As shown in Table 5.35, the square root of the AVE of each construct was greater than the correlation with other constructs in the model; this finding satisfied the discriminant validity, based on the Fornell-Larcker criterion (Fornell & Larcker, 1981).

Table 5.35 Comparisons of correlation between constructs and square root of AVE for discriminant validity (Sensor model: step3)

Constructs	TD	PR	EX	DE	PPD	PES
TD	**0.759**					
PR	0.189	**0.778**				
EX	0.436	0.082	**0.934**			
DE	-0.261	0.126	0.055	**0.834**		
PPD	0.323	0.052	0.365	-0.207	[a]**1.000**	
PES	-0.021	-0.071	0.026	0.207	0.363	[a]**1.000**

Note.a: Single item construct; Bold diagonal values: The square root of average variance extracted; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

All HTMT values were smaller than the 0.85 threshold, as suggested by Kline (2015). Further, according to Henseler et al.'s (2015) guideline, 95% confidence intervals of HTMT through bootstrapping analysis did not include 1 in any of the pathways between the two constructs. These conditions were satisfied, as shown in Table 5.36. Thus, the discriminant validity was satisfied for the measurement model.

Table 5.36 Heterotrait–monotrait ratio of correlation (Sensor model: step3)

	Original Sample	Sample Mean	Bias	95% Confidence Intervals	
				2.50%	97.50%
TD → DE	0.450	0.484	0.034	0.172	0.664
TD → EX	0.488	0.485	-0.003	0.255	0.683
TD → PPD	0.392	0.391	-0.001	0.187	0.589
TD → PES	0.186	0.209	0.024	0.052	0.352
TD → PR	0.366	0.594	0.227	0.053	0.562
PR → DE	0.291	0.428	0.137	0.077	0.420
PR → EX	0.156	0.305	0.149	0.034	0.274
PR → PPD	0.117	0.271	0.155	0.004	0.224
PR → PES	0.128	0.261	0.133	0.003	0.263
EX → DE	0.108	0.154	0.046	0.034	0.167
PPD → DE	0.214	0.227	0.013	0.043	0.408
PPD → EX	0.374	0.362	-0.012	0.133	0.580
PES → DE	0.242	0.247	0.005	0.073	0.436
PES → EX	0.071	0.129	0.058	0.006	0.114
PES → PPD	0.363	0.359	-0.004	0.172	0.521

Note.TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Structural model: The results of the PLS-SEM bootstrapping to assess the structural model are summarized in Tables 5.37 through 5.40. Table 5.37 summarizes how much variance of exogenous latent variables can be explained in the model based on the R^2 value estimations. In the case of EX and PPD, the acceptable amounts of variance (19.0% and 18.5%, respectively) were explained based on the reported R^2 value in many social sciences studies investigating human behavior (Falk

& Miller, 1992; Moksony, 1999). Falk and Miller (1992) suggested that the variance explained for endogenous constructs should be greater than 10%, as a rule of thumb. However, only 1.8% and 4.3% variances were experienced for DE and PES, respectively.

Table 5.37 Coefficient of determination (Sensor model: step3)

	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
EX	0.190	0.214	0.069	2.765	0.006
DE	0.018	0.059	0.044	0.410	0.682
PPD	0.185	0.203	0.080	2.311	0.021
PES	0.043	0.070	0.047	0.922	0.356

Note. EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The criteria for identifying the effect size f^2 are 0.02, 0.15, and 0.35, indicating small, medium, and large effects of the corresponding extrinsic variables (Cohen, 1988). At the structural level, the effect size of PR on EX, PR on DE, EX on DE, and EX on PES, was small, based on the guideline (Table 5.38).

Table 5.38 Result of f^2 effect size (Sensor model: step3)

	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
TD → EX	0.226	0.251	0.115	1.967	0.049
PR→ EX	0.000	0.014	0.019	0.000	1.000
PR→ DE	0.015	0.047	0.043	0.350	0.726
EX →DE	0.002	0.017	0.024	0.086	0.931
EX → PPD	0.174	0.197	0.133	1.311	0.190
EX → PES	0.000	0.016	0.024	0.010	0.992
DE → PES	0.045	0.058	0.052	0.862	0.389
DE →PPD	0.063	0.084	0.066	0.959	0.338

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.39 Significance testing results of the structural model path coefficient (Sensor model: step3)

	Path Coefficients	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.436	5.076	0.000	0.240	0.582	Yes
PR → EX	0.000	0.002	0.998	-0.225	0.186	No
PR → DE	0.123	0.733	0.464	-0.354	0.309	No
EX → DE	0.045	0.379	0.705	-0.191	0.273	No
EX → PPD	0.377	3.070	0.002	0.116	0.591	Yes
EX → PES	0.015	0.122	0.903	-0.263	0.225	No
DE → PES	0.207	1.868	0.062	-0.039	0.394	Marginally Yes
DE → PPD	-0.228	2.103	0.036	-0.411	0.020	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.40 Significance testing results of the total effects (Sensor model: step3)

	Total effects	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.436	5.076	0.000	0.240	0.582	Yes
TD → DE	0.020	0.364	0.716	-0.090	0.128	No
TD → PPD	0.160	2.324	0.020	0.035	0.300	Yes
TD → PES	0.011	0.176	0.861	-0.110	0.132	No
PR → EX	0.000	0.002	0.998	-0.225	0.186	No
PR → DE	0.123	0.735	0.463	-0.354	0.309	No
PR → PPD	-0.028	0.537	0.591	-0.123	0.075	No
PR → PES	0.025	0.600	0.548	-0.079	0.092	No
EX → DE	0.045	0.379	0.705	-0.191	0.273	No
EX → PPD	0.367	3.181	0.001	0.129	0.571	Yes
EX → PES	0.024	0.180	0.857	-0.273	0.258	No
DE → PPD	-0.228	2.103	0.036	-0.411	0.020	Yes
DE → PES	0.207	1.868	0.062	-0.039	0.394	Marginally Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

As shown in Figure 5.3 and Table 5.41, the path between TD and EX, with a statistically significant (t = 5.076; p < 0.001) β coefficient of 0.436, does support *Hypothesis 1*. The path between PR and EX, with a statistically insignificant (t = 0.002; p = 0.998) coefficient of 0.000, does not support *Hypothesis 2*. The effect of PR on DE was also not significant (β = 0.123; t = 0.733; p = 0.464); thus, *Hypothesis 3* was not supported. EX did not have an obvious effect on DE (β = 0.045; t = 0.379; p = 0.705); therefore, *Hypothesis 4* was not supported. The reverse influence describing the linkage of EX to PPD was significant (β = 0.377; p < 0.05; t = 3.070), which confirmed that *Hypothesis 5*a* was supported with a reverse direction of the association. On the other hand, the effect of EX on PES was not significant (β = 0.015; t = 0.122; p = 0.903), which means that *Hypothesis 5*b* was not supported. The structural path link between DE and PPD, with an acceptable significance (p < 0.05; t = 2.103), indicates that *Hypothesis 6*a* was supported, but the direction of association was a negative path coefficient (β) of -0.228. The effect of DE on PES, with a coefficient of 0.207, was at the acceptable borderline of significance (t = 1.868; p < 0.1), which means that *Hypothesis 6*b* was marginally supported.

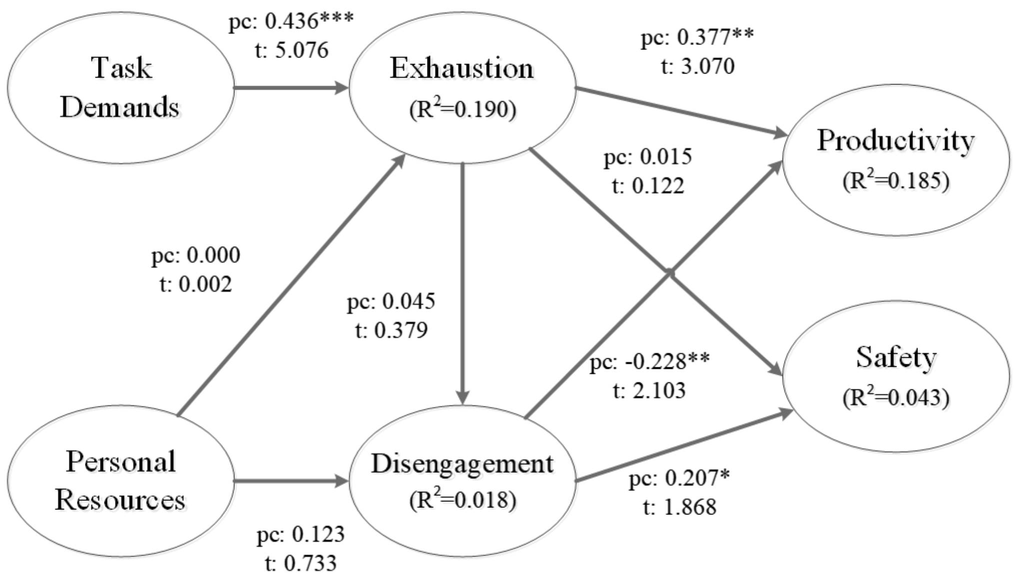

Figure 5.3 Path diagram for the model with survey measurements (pc: Path coefficient; t: t statistic; ***: p<0.001; **: p<0.05; *: p<0.1; Two-tailed tests)

Table 5.41 Hypothesis testing results in the sensor model (Sensor model: step3)

Hypot heses	Constructs and direction of relationships	Standardized path coefficient (β)	*t*-Value	*p*-Value	Inference
H1	TD→EX (+)	0.436	5.076	0.000	Supported
H2	PR→EX (-)	0.000	0.002	0.998	Not supported
H3	PR→DE (-)	0.123	0.733	0.464	Not supported
H4	EX→DE (+)	0.045	0.379	0.705	Not supported
H5*a	EX→PPD (-)	0.377	3.070	0.002	Supported (Reverse)
H5*b	EX→PES (-)	0.015	0.122	0.903	Not supported
H6*a	DE→PPD (-)	-0.228	2.103	0.036	Supported
H6*b	DE→PES (-)	0.207	1.868	0.062	Marginally supported (Reverse)

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

5.2.3 Survey and Sensor Measurements Combined Model

<u>Measurement model:</u> For measuring each individual construct, the addition of sensor and survey measurement items significantly lowered indicator reliability as well as convergent validity. Thus,

a decision was made to measure single constructs using a single measurement method (i.e., sensor vs. survey measurement method). In conclusion, the TD and EX were only measured by sensor measurements, and PR and DE were only measured by survey measurements. The PPD and PES were measured using objective measurement methods via video recording (for productivity) and sensors (for ergonomics safety behavior). This decision enabled the selection of the survey and sensor combined model, which satisfied the reliability and validity of its final measurement model. Table 5.42 shows that Cronbach's alpha value was greater than the benchmark value of 0.7, indicating that an acceptable level of internal consistency reliability was achieved for all constructs. The Cronbach's alpha for TD was close to 0.7. The CR value was shown to be higher than the minimum standard value of 0.7. All the AVE values were greater than 0.5, indicating that the convergent validity was acceptable.

Table 5.42 Reliability and convergent validity (Combined model: final model)

Constructs	Cronbach's α	Composite Reliability	AVE
TD	0.674	0.803	0.577
PR	0.738	0.846	0.648
EX	0.951	0.965	0.873
DE	0.792	0.877	0.705
PPD	[a]1.000	[a]1.000	[a]1.000
PES	[a]1.000	[a]1.000	[a]1.000

Note. a: Single item construct; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

In terms of the indicators measuring the disengagement construct, the three items (i.e., de_invitem17, de_invitem21, de_invitem22) having acceptable outer loadings in the previous assessment of the sensor model were included in the combined model. The results in Table 5.43 show that the indicators' outer loadings of the combined survey and sensor measurement satisfied the criterion that outer loadings should be greater than 0.70.

Table 5.43 Analysis of cross-loadings of the latent variables (Combined model: final model)

Measured variables	Correlations with respect to the latent variables					
	TD	PR	EX	DE	PPD	PES
td_Enerkcal	**0.745**	0.181	0.239	-0.394	0.333	-0.160
td_lnRhr	**0.757**	0.083	0.430	-0.057	0.226	0.106
td_lnWenerkcal	**0.776**	0.208	0.245	-0.296	0.191	-0.090
pr_Ghnbs	0.271	**0.879**	0.078	-0.483	0.272	0.003
pr_Pfnbs	0.091	**0.769**	0.073	-0.307	0.165	0.109
pr_Rpnbs	0.018	**0.762**	-0.131	-0.291	0.197	0.140
eh_invHrvhffft	0.357	0.001	**0.945**	0.028	0.357	0.030
eh_invHrvlffft	0.375	-0.001	**0.912**	0.108	0.340	0.113
eh_invRmss	0.435	0.072	**0.904**	-0.041	0.302	-0.081
eh_invSdnn	0.455	0.027	**0.975**	0.055	0.363	0.035
[b]de_invitem17	-0.192	-0.466	0.098	**0.856**	-0.200	0.202
[b]de_invitem21	-0.218	-0.365	0.053	**0.900**	-0.198	0.136
[b]de_invitem22	-0.310	-0.321	-0.081	**0.756**	-0.083	0.206
pf_Productivity	0.323	0.272	0.365	-0.198	**[a]1.000**	0.363
pf_lnErgoRatio60	-0.021	0.084	0.026	0.215	0.363	**[a]1.000**

Note. a: Single item construct; b: survey measurements used (no indicators measured by the sensor for the disengagement construct); Bold texts: the indicators' outer-loadings are greater than 0.7; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The discriminant validity was obtained because the square root of the AVE of each reflective construct was greater than the correlation with other constructs in the model, as shown in Table 5.44.

Table 5.44 Comparisons of correlation between constructs and square root of AVE for discriminant validity (Combined model: final model)

	TD	PR	EX	DE	PPD	PES
TD	**0.759**					
PR	0.187	**0.805**				
EX	0.435	0.027	**0.934**			
DE	-0.276	-0.468	0.041	**0.840**		
PPD	0.323	0.272	0.365	-0.198	**[a]1.000**	
PES	-0.021	0.084	0.026	0.215	0.363	**[a]1.000**

Note. a. Single item construct; Bold diagonal values: The square root of average variance extracted; TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The results of bootstrapping for the HTMT, with the number of bootstrapping sub-samples set to 5000, are summarized in Table 5.45. As suggested by Kline (2015), all HTMT values were lower than the maximum acceptable threshold of 0.85. Further, the confidence intervals of HTMT estimated by bootstrapping reported that the confidence intervals did not include 1 in any of the cases, based on Henseler et al.'s (2015) guideline. Thus, the discriminant validity was satisfied for the measurement model.

Table 5.45 Heterotrait–monotrait ratio of correlation (Combined model: final model)

	Original Sample	Sample Mean	Bias	95% Confidence Intervals	
				2.50%	97.50%
TD → DE	0.450	0.486	0.036	0.176	0.664
TD → EX	0.488	0.483	-0.005	0.266	0.690
TD → PPD	0.392	0.390	-0.001	0.184	0.582
TD → PES	0.186	0.209	0.023	0.051	0.356
TD → PR	0.240	0.358	0.118	0.064	0.367
PR → DE	0.569	0.577	0.008	0.323	0.791
PR → EX	0.138	0.174	0.035	0.048	0.232
PR → PPD	0.304	0.308	0.004	0.125	0.484
PR → PES	0.120	0.185	0.065	0.013	0.277
EX → DE	0.108	0.154	0.046	0.034	0.164
PPD → DE	0.214	0.227	0.013	0.046	0.407
PPD → EX	0.374	0.361	-0.012	0.126	0.576
PES → DE	0.242	0.247	0.005	0.071	0.439
PES → EX	0.071	0.128	0.057	0.007	0.118
PES → PPD	0.363	0.362	0.000	0.162	0.522

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Structural model: The results of the PLS-SEM bootstrapping to assess the structural model evaluation are summarized in Tables 5.46 through 5.50. The coefficient of determination presented that the variances explained for EX, DE, and PPD constructs were 19%, 22%, and 18%, respectively. The R^2 value for PES was 4.7%, implying that it was lower than the acceptable R^2 value of 10%, as suggested by Falk and Miller (1992).

Table 5.46 Coefficient of determination (Combined model: final model)

	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
EX	0.193	0.219	0.075	2.555	0.011
DE	0.222	0.261	0.085	2.613	0.009
PPD	0.179	0.196	0.081	2.201	0.028
PES	0.047	0.070	0.045	1.027	0.304

Note. EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

The criteria for identifying the effect size f^2 are 0.02, 0.15, and 0.35, indicating small, medium, and large effects of the corresponding constructs (Cohen, 1988). As a result, in Table 5.47, it was found that the effect size of the construct TD on the endogenous latent variable EX was larger than that of PR, and the effect size of TD on EX was 0.15 or more. The effect of the construct PR on the endogenous latent variable DE was larger than that of EX. The effect of PR on DE was 0.282, which was also 0.15 or more, but less than 0.35. The effect of the construct EX on the endogenous latent variable PPD was larger than that of DE, and the effect on PPD of EX was 0.169, which was also 0.15 or more, but less than 0.35. The effect of DE on PES was larger than that of EX. The effect of DE on PES was 0.048.

Table 5.47 Result of f^2 effect size (Combined model: final model)

	Original Sample	Sample Mean	Standard Deviation	*t*-Value	*p*-Value
TD → EX	0.238	0.278	0.130	1.833	0.067
PR → EX	0.004	0.020	0.029	0.133	0.894
PR → DE	0.282	0.355	0.163	1.730	0.084
EX→ DE	0.004	0.026	0.034	0.109	0.913
EX → PPD	0.169	0.192	0.132	1.287	0.198
DE → PPD	0.056	0.074	0.061	0.912	0.362
EX → PES	0.000	0.016	0.024	0.013	0.989
DE → PES	0.048	0.058	0.050	0.972	0.331

Note.TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.48 Significance testing results of the structural model path coefficient (Combined model: final model)

	Path Coefficients	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.446	4.935	0.000	0.228	0.596	Yes
PR → EX	-0.056	0.521	0.602	-0.274	0.150	No
PR → DE	-0.469	5.258	0.000	-0.609	-0.237	Yes
EX → DE	0.054	0.436	0.663	-0.221	0.257	No
EX → PPD	0.373	3.090	0.002	0.107	0.586	Yes
EX → PES	0.018	0.146	0.884	-0.244	0.233	No
DE → PES	0.215	2.172	0.030	0.018	0.407	Yes
DE → PPD	-0.214	2.126	0.034	-0.394	0.003	Yes

Note.TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance

Table 5.49 Significance testing results of the total effects (Combined model: final model)

	Total effects	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.446	4.935	0.000	0.228	0.596	Yes
TD → DE	0.024	0.415	0.678	-0.109	0.122	No
TD → PPD	0.161	2.252	0.024	0.029	0.303	Yes
TD → PES	0.013	0.207	0.836	-0.111	0.136	No
PR → EX	-0.056	0.521	0.602	-0.274	0.150	No
PR → DE	-0.472	5.093	0.000	-0.619	-0.235	Yes
PR → PPD	0.080	1.129	0.259	-0.070	0.205	No
PR → PES	-0.102	1.964	0.050	-0.209	-0.007	Yes
EX → DE	0.054	0.436	0.663	-0.221	0.257	No
EX → PPD	0.362	3.130	0.002	0.109	0.559	Yes
EX → PES	0.029	0.218	0.828	-0.264	0.261	No
DE → PES	0.215	2.172	0.030	0.018	0.407	Yes
DE → PPD	-0.214	2.126	0.034	-0.394	0.003	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

As summarized in Figure 5.4 and Table 5.50, the effect of TD on EX, with a coefficient of 0.446 at the acceptable significance level (t = 4.935; p < 0.001;), supports *Hypothesis 1*. The path between PR and EX, with a statistically insignificant (t = 0.521; p = 0.602;) coefficient of -0.056, does not support *Hypothesis 2*. The path between PR and DE, with a statically significant (t = 5.258; p < 0.001;) coefficient of -0.469, supports *Hypothesis 3*. The effect of EX on DE, with a coefficient of 0.436, was at a statistically insignificant level (t = 0.436; p = 0.663); thus, *Hypothesis 4* was not supported. The structural path linking EX and PPD, with an acceptable significance level with an alpha level of 0.05 (β = 0.373; t = 3.090; p < 0.05), does support *Hypothesis 5*a*. However, the direction of association was reversed, with a path coefficient of 3.090. The effect of EX on PES, with a coefficient of 0.018 (t = 0.146; p = 0.884), shows that *Hypothesis 5*b* was not supported. The hypothetical paths between DE and PPD as well as between DE and PES, with coefficients of -0.214 and 0.215 at the acceptable significance level (t = 2.126; p = 0.034 and t = 2.172; p = 0.030, respectively), show that *Hypothesis 6*a* and *Hypothesis 6*b* were supported.

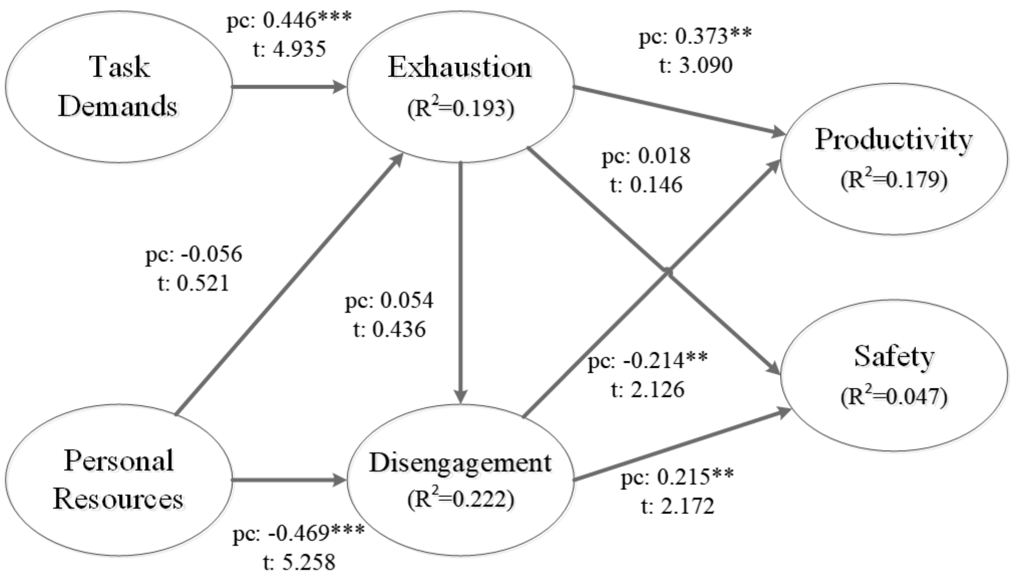

Figure 5.4 Path diagram for the model combining survey and sensor measurements (pc: Path coefficient; t: t statistic; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

Table 5.50 Hypothesis testing results in the full model combined survey and sensor measurements (Combined model: final model)

Hypotheses	Constructs and direction of relationships	Standardized path coefficient (β)	*t*-Value	*p*-Value	Inference
H1	TD→EX (+)	0.446	4.935	0.000	Supported
H2	PR→EX (-)	-0.056	0.521	0.602	Not supported
H3	PR→DE (-)	-0.469	5.258	0.000	Supported
H4	EX→DE(+)	0.054	0.436	0.663	Not supported
H5*a	EX→PPD (-)	0.373	3.090	0.002	Supported (reverse)
H5*b	EX→PES (-)	0.018	0.146	0.884	Not supported
H6*a	DE→PPD (-)	-0.214	2.126	0.034	Supported
H6*b	DE→PES (-)	0.215	2.172	0.030	Supported (reverse)

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

5.2.4 Comparison of Predictive Relevance and Coefficient of Determination between Survey Model, Sensor Model, and Combined Model

The predictive relevance was evaluated using Stone-Geisser's Q^2, as a criterion for the accuracy of the prediction (Geisser, 1974; Stone, 1974). The predictive relevance (Q^2) value of the latent variable in the structural model was greater than 0, indicating the predictability of the path model in the construct (Hair et al., 2017). Q^2 was calculated through a blindfolding procedure using omission distance (*D*).

Blindfolding is a sample reuse technique that estimates the coefficients using the remaining data points, omitting every *D*th data point in the endogenous construct (Hair et al., 2017). Omitted data points become missing values and are replaced by mean values at the time of analysis, and the next coefficient-value is used to predict the missing data point (Chin 1998). Blindfolding is a process that iterates until each data point is missing and is re-estimated by the model; the difference between the omitted data point and the predicted data point is used to calculate Q^2 (Hair et al, 2017). The value of *D* should be selected based on the criterion that the number of samples used for model estimation divided by *D* should not be an integer (Hair et al., 2017). Since there were 80 observations in this study, the D was set to 7 (i.e., 80/7 = 11.4) during blindfolding in the SmartPLS program. Q^2 is calculated based on the following equation 5.1 (Hair et al. 2017):

$$Q^2 = 1 - \frac{SSE}{SSO} \tag{5.1}$$

where *SSE* is the sum of the squared prediction errors and *SSO* is the sum of the squared observations. An estimated Q^2 greater than 0 indicates that the model has predictability for a particular construct (Henseler, Ringle, & Sinkovics, 2009). Thus, if Q^2 is 0 or less, then there is a problem with predictability.

The results of the analysis of predictive relevance through blindfolding are summarized for three models—survey model, sensor model, and combined model—in Table 5.56. In the survey model, the Q^2 of PPD was smaller than 0, and the Q^2 values of DE and PES were smaller than 0 in the sensor model (Table 5.51). Concerning the combined model, in Table 5.56, there is no problem in predictive relevance for EX, DE, and PPD, where Q^2 is greater than 0. However, the Q^2 value for PES is 0, which indicates that there is a limitation with predictive relevance.

Table 5.51 Summary of predictive relevance among three different models (Q^2 value)

	Survey model			Sensor model			Combined Model		
	SSO	SSE	Q^2	SSO	SSE	Q^2	SSO	SSE	Q^2
EX	320.000	232.027	0.275	320.000	273.980	0.144	320.000	272.071	0.150
DE	480.000	426.986	0.110	240.000	241.186	-0.005	240.000	207.867	0.134
PPD	80.000	82.500	-0.031	80.000	69.266	0.134	80.000	69.433	0.132
PES	80.000	78.149	0.023	80.000	80.611	-0.008	80.000	80.007	0.000

Note. SSO: Sum of the squared observations; SSE: Sum of the squared prediction errors.

Table 5.52 compares the results of the R^2 estimations of the tested models in the three different scenarios (i.e., survey model, sensor model, and combined model) presented above. When comparing the predictive power according to the R^2 comparison, EX and DE showed the highest level through survey measurements in the survey model. The sensor model improved the predictive power of the PPD, but it also lowered the predictive power of the other constructs (i.e., EX, DE, and PES). In the combined model, the predictive power of EX and DE were lower than that in the survey model. However, the overall balanced prediction performance, which the results of variance explained for EX, DE, and PPD, were greater than 10%. The prediction performance of PES construct was low in that the results of variance explained were less than 10% in all three models.

Table 5.52 Summary of predictive power among three different models (R^2 value)

	Survey model	Sensor model	Combined Model
EX	0.489	0.190	0.193
DE	0.255	0.018	0.222
PPD	0.019	0.185	0.179
PES	0.072	0.043	0.047

Note. EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Since the number of sample sizes and exogenous/endogenous variables were the same for the survey, sensor, and combined models, only the R^2 values were compared in Table 5.52 (i.e., adjusted R^2 and f^2 were not compared) . The rule of thumb for R^2 is that 0.75 is large, 0.50 is medium, and 0.25 is weak. However, the evaluation criteria differ depending on the complexity of the research field and the model, and 0.20 for R^2 in consumer behavior research is evaluated as a high R^2 value (Hair et al., 2017). According to Falk and Miller (1992), the variance explained for endogenous constructs that is greater than 0.1 is the acceptable threshold. The R^2 of the model using PLS-SEM, in the construction management field, was reported to be around 0.2 (e.g., Song et al., 2017). The current research studied the behavior of workers in relation to safety or productivity, such as in consumer behavior; thus, an R^2 of 0.20 is assumed to be a high coefficient of determination.

5.3. Moderation effect

Using the product indicator option (interaction term created by multiplying the moderator's indicators with the exogenous latent variable's indicators) of the SmartPLS 3.0 software, the moderating effects of changing the direction or the strength of the influence of personal resources on exhaustion of task demands were analyzed. The conceptual framework of the product terms of the moderating effect in the model is shown in Figure 5.5.

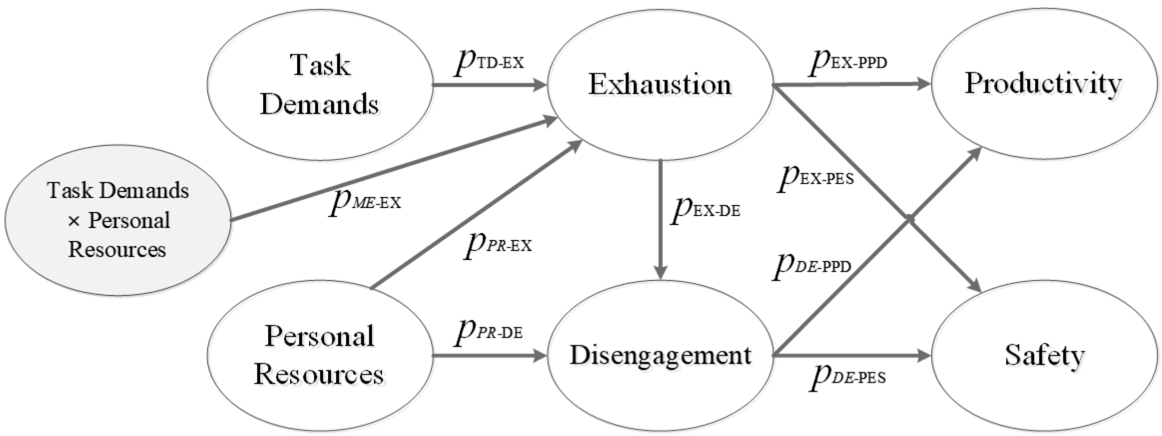

Figure 5.5. Interaction term in moderation

The product indicator option in the SmartPLS 3.0 was used for interaction analysis. The product indicator approach created a latent interaction variable by multiplying indicators from the predictor latent variable and from the moderator variable (Chin, Marcolin, & Newsted, 2003). The significance of the effect of the interaction term on the endogenous construct (i.e., exhaustion) was assessed through the bootstrapping process. The interactions between TD, measured by the four survey indicators (i.e., td_Effort, td_Frustrationl, td_Physicald, and td_Temporald), and PR, measured by three survey indicators, (i.e., pr_Ghnbs, pr_Pfnbs, and pr_Rpnbs), were analyzed. The t-value of the interaction term was 0.882, and the p-value was 0.378. Thus, at the significance level of 0.05, the hypothesis (*Hypothesis H2**) that there is an interaction effect of PR in relation to TD and EX was not supported. Table 5.53 summarizes the path coefficients when only survey data are included in the data analysis.

Table 5.53 Results of Path Analysis in the survey model

	Path Coefficients	Standard Deviation	*t*-Value	*p*-Value	Significance (p<0.05)?
TD → EX	0.337	0.086	3.894	0.000	Yes
PR → DE	-0.087	0.155	0.566	0.572	No
PR → EX	-0.509	0.067	7.613	0.000	Yes
ME → EX	**0.139**	**0.158**	**0.882**	**0.378**	**No**
EX → DE	0.446	0.115	3.866	0.000	Yes
EX → PPD	-0.104	0.153	0.681	0.496	No
EX→ PES	-0.165	0.115	1.438	0.151	No
DE → PPD	-0.051	0.146	0.346	0.729	No
DE → PES	0.309	0.109	2.820	0.005	Yes

Note. ME in bold text: Moderating Effect.

Finally, the interactions of TD, three sensor indicators (i.e., td_Enerkcal, td_InRhr, and td_InWenerkcal), and PR were analyzed by two sensor indicators (i.e., pr_lnHrr and pr_lnTotalsl) As a result, the t-value of the interaction term and EX path was 0.401, and the p-value was 0.689. Therefore, the adjustment effect of PR on the relationship between TD and EX was not supported at the significance level of 0.05. Thus, *Hypothesis H2** was not supported. Table 5.54 summarizes the path coefficients when only sensor data is included in the data analysis.

Table 5.54 Results of path analysis in the sensor model

	Path Coefficients	Standard Deviation	*t*-Value	*p*-Value	Significance (p<0.05)?
TD → EX	0.415	0.085	4.888	0.000	Yes
PR → EX	0.023	0.105	0.219	0.827	No
PR → DE	0.123	0.168	0.730	0.466	No
ME → EX	**-0.085**	**0.212**	**0.401**	**0.689**	**No**
EX → DE	0.045	0.119	0.382	0.703	No
EX→ PPD	0.377	0.124	3.048	0.002	Yes
EX → PES	0.015	0.124	0.121	0.904	No
DE → PPD	-0.228	0.107	2.135	0.033	Yes
DE → PES	0.207	0.110	1.885	0.059	Marginally Yes

Note. ME in bold text: Moderating Effect

Table 5.55 summarizes the path coefficients when both surveys and sensor data are included in the data analysis. As a result, the t-value of the interaction term and exhaustion path was 0.304, and the p-value was 0.761. Thus, at the significance level of 0.05, the adjustment effect of personal resources in relation to TD and EX was not supported.

Table 5.55 Results of path analysis in the combined model

	Path Coefficients	Standard Deviation	*t*-Value	*p*-Value	Significance ($p<0.05$)?
TD → EX	0.431	0.095	4.538	0.000	Yes
PR → EX	-0.064	0.140	0.458	0.647	No
PR → DE	-0.469	0.087	5.385	0.000	Yes
ME → EX	**-0.044**	**0.145**	**0.304**	**0.761**	**No**
EX → DE	0.054	0.125	0.429	0.668	No
EX → PPD	0.373	0.122	3.065	0.002	Yes
EX→ PES	0.017	0.121	0.145	0.885	No
DE → PES	0.215	0.098	2.192	0.028	Yes
DE → PPD	-0.214	0.103	2.070	0.038	Yes

Note. ME in bold text: Moderating Effect.

Overall, concerning testing the significance of the coefficient of the interaction term, the moderating effect of personal resources on the relationship between task demands and exhaustion was not statistically significant for all the three models (i.e., survey, sensor, and combined models).

5.4 Mediating effect

In order to satisfy the minimum requirement of the sample size of the PLS-SEM, following the “10 times rule” (Barclay et al., 1995), the mediating effect analysis was performed after removing the statistically insignificant paths from the analysis in the previous section (i.e., paths between PR and EX, EX and DE, and EX and PES) of the combined model. Subsequently, the direct paths between the lowest-order of the construct (e.g., TD) and the highest-order of the construct (e.g., PPD) were directly connected (Figure 5.6). Since the sample size obtained was 80, a maximum of eight structural paths directed to a particular construct can be modeled. Eventually, in the relationship between TD and PPD, whether EX plays a mediating effect was analyzed. Additionally, the mediating effect of DE in the relationship between PR and PPD was analyzed. Finally, the mediating effect of DE in the relationship between PR and PES was tested using the SmartPLS 3.0 software. The results of the analysis, including path coefficients, specific indirect effects, and total effects, are summarized in Tables 5.56 to 5.58.

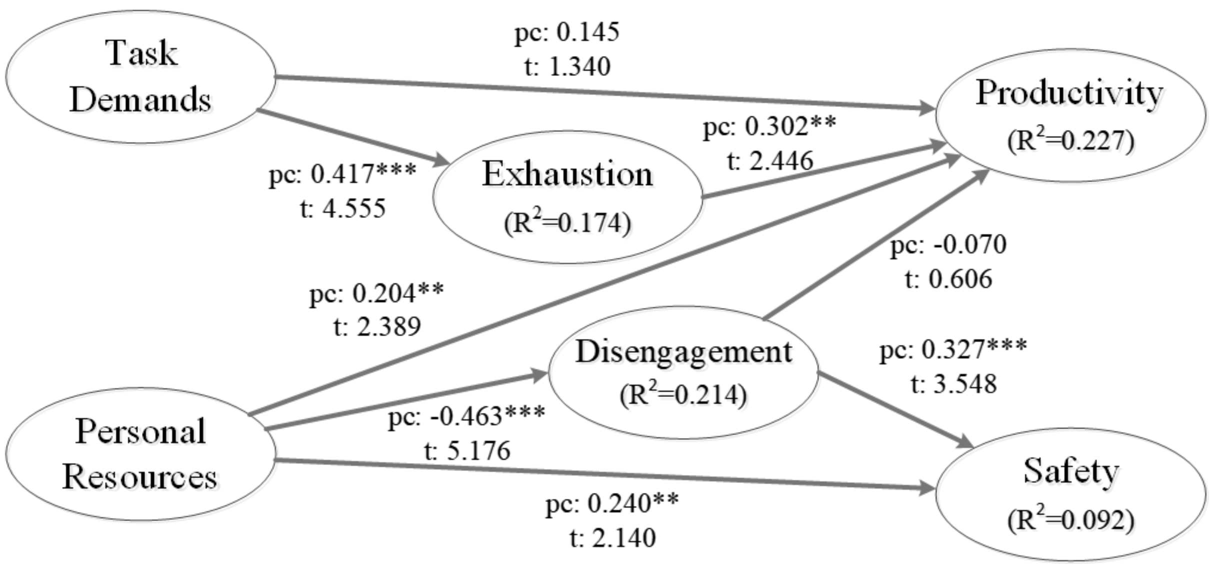

Figure 5.6 Path diagram for the mediation model (pc: Path coefficient; t: t statistic; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

Table 5.56 Path coefficient (mediating effect)

	Path Coefficients	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.417	4.555	0.000	0.184	0.561	Yes
TD → PPD	0.145	1.340	0.180	-0.093	0.337	No
PR → DE	-0.463	5.176	0.000	-0.596	-0.209	Yes
PR → PPD	0.204	2.389	0.017	0.008	0.350	Yes
PR → PES	0.240	2.140	0.032	0.006	0.449	Yes
EX → PPD	0.302	2.446	0.014	0.057	0.538	Yes
DE → PPD	-0.070	0.606	0.545	-0.292	0.162	No
DE → PES	0.327	3.548	0.000	0.119	0.489	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.57 Specific indirect effects (mediating effect)

	Original Sample	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX → PPD	0.126	1.888	0.059	0.017	0.28	Marginally Yes
PR → DE → PPD	0.033	0.565	0.572	-0.077	0.155	No
PR → DE → PES	-0.151	3.051	0.002	-0.252	-0.061	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

Table 5.58 Total effects (mediating effect)

	Original Sample	*t*-Value	*p*-Value	95% Confidence Intervals		Significance (p<0.05)?
				2.50%	97.50%	
TD → EX	0.417	4.555	0.000	0.184	0.561	Yes
TD → PPD	0.271	2.720	0.007	0.047	0.442	Yes
PR → DE	-0.463	5.176	0.000	-0.596	-0.209	Yes
PR → PPD	0.237	2.735	0.006	0.042	0.387	Yes
PR → PES	0.089	0.748	0.455	-0.141	0.321	No
EX → PPD	0.302	2.446	0.014	0.057	0.538	Yes
DE → PPD	-0.070	0.606	0.545	-0.292	0.162	No
DE → PES	0.327	3.548	0.000	0.119	0.489	Yes

Note. TD: Task Demands; PR: Personal Resources; EX: Exhaustion; DE: Disengagement; PPD: Productivity Performance; PES: Safety Performance.

To present the outcome of the analysis of mediating effects clearly, diagrams showing each mediation effect were created separately; these effects are presented in Figure 5.7 through Figure 5.9. As depicted in Figure 5.7, TD, EX, and PPD appeared to be fully mediated models. In other words, the direct effect from TD to PPD is insignificant (β = 0.145; p = 0.180; t = 1.340), but the relationships from TD to EX (β = 0.417; p < 0.001; t = 4.555) and from EX to PPD (β = 0.302; p < 0.05; t = 2.446) are both statistically significant.

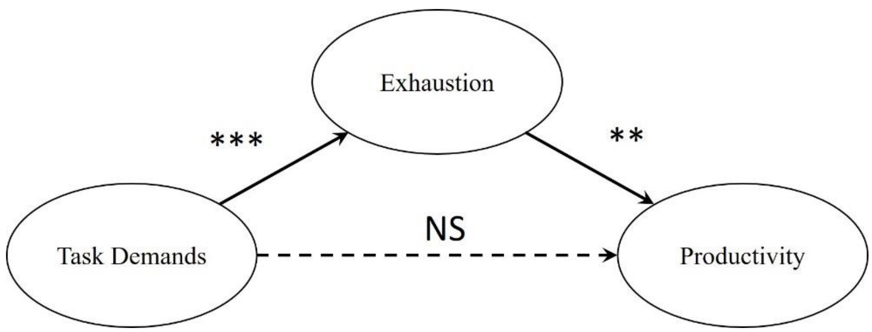

Figure 5.7 Mediating effect of exhaustion on the relationship between task demands and productivity (NS: not significant; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

The relationship between PR, DE, and PPD was found to have no mediating effect (Figure 5.8). In other words, direct effects from PR to PPD were significant (β = 0.417; p < 0.001; t = 4.555), but there was no mediating effect of PR through DE to PPD. This is because the relationship of DE to PPD was not statistically significant (β = -0.070; p = 0.545; t = 0.606), even though the negative relationship between PR and DE was statistically significant (β = -0.463; p < 0.001; t = 5.176).

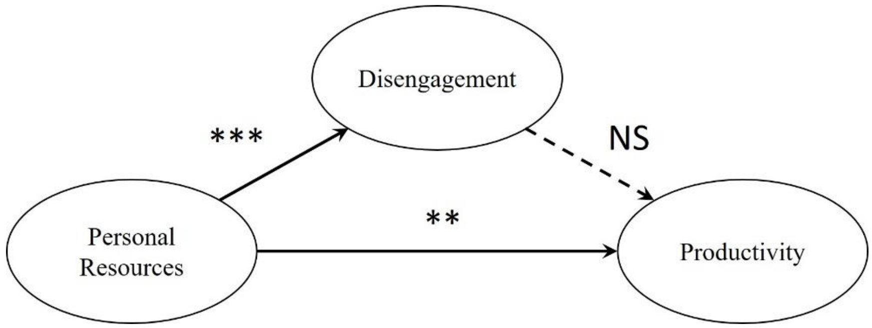

Figure 5.8 Mediating effect of disengagement on the relationship between personal resources and productivity (NS: not significant; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

The relationship between PR, DE, and PES appeared as a partial mediation model, as shown in Figure 5.9. In other words, the relationship from PR to DE (β = -0.463; $p < 0.001$; t = 5.176) and from DE to PES (β = 0.327; $p < 0.001$; t = 3.548) was more significant than the direct effects from PR to PES (β = 0.240; $p < 0.05$; t = 2.140). In this context, partial mediation implies that simultaneously managing a subject's personal resources and disengagement is important for managing the impact of personal resources on safety performance.

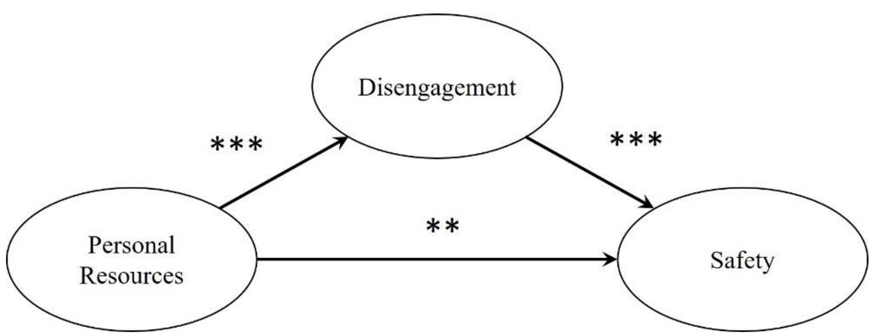

Figure 5.9 Mediating effect of disengagement on the relationship between personal resources and safety (NS: not significant; ***: p<0.001; **: p<0.05; *: p<0.10; Two-tailed tests)

Chapter 6 Discussion

This dissertation explored the relationship between demands, resources, burnout, and performance at the task level. It also developed protocols for the application of wearable sensors in construction workforce management and activities involving the handling of construction material. Of the existing phases of burnout, this study focused on the acute onset of burnout (Golembiewski & Munzenrider, 1988) to understand construction workers' daily burnout experiences and their consequences, as introduced by Xanthopoulou and Meier (2014). The understanding and measurement of acute burnout are important research topics because, as emphasized by Xanthopoulou and Meier (2014), failure to recover from daily burnout eventually builds up, leading to further chronic burnout that eventually effects on the work-related and health consequences adversely. In this dissertation research, acute burnout was measured through the presence of exhaustion and disengagement, which are two core dimensions specified in the Oldenburg Burnout Inventory (Demerouti & Nachreiner, 1999; Demerouti et al., 2001).

6.1 General Discussion

Previous research utilizing the job demands-resources (JD-R) model (e.g., Li et al., 2013; Nahrgang et al., 2011) has contributed to the development of an understanding of the engagement and burnout of workers. However, previous research method has depended on the use of surveys, such as the Maslach Burnout Inventory (Maslach et al., 1986) and the Oldenburg Burnout Inventory (Demerouti & Nachreiner, 1999). Moeller, Ivcevic, White, Menges, and Brackett (2018) noted that a subject's acquiescence response style in burnout research may affect the study results. In the current study, the selected research constructs were measured both objectively by using wearable technology and subjectively by using survey instruments. This study investigates which wearable sensor measurements are suitable for application of the JD-R, burnout, and performance models. It aims to predict the endogenous latent variables (i.e., exhaustion, engagement, safety performance, and productivity) that are of major interest in the field of human resource management for achieving the optimal performance of construction contractors. The performance construct was further converted into separate constructs which measure productivity and safety and formed the final evaluation model. All three models developed in the research, namely, the (1) **survey model**, (2) **sensor model**, and (3) **combined model** (both survey and sensors measurements include), displayed low predictive performance regarding the safety performance (PES) construct. The combined model demonstrated higher predictive performance regarding the productivity performance (PPD) construct than either of the survey or sensor models. Overall, the **combined model** achieved an acceptable level (i.e., greater than 10% explained variance) of predicted performance for all endogenous constructs from the perspective of human behavior research in social and management science. This finding is in line with the result of a previous study (Lee, 2018) illustrating that both survey and sensor measurements are necessary to predict construction workers' perceived fatigue status in a logistic regression model. For these reasons, the following sections discuss the results of the hypothesis testing in the final **combined model**.

Based on the hypothesis testing using PLS-SEM in the **combined model**, supported *Hypothesis 1 (H1)* found that an increase in task demands is related to increased exhaustion. This finding confirms the previous results of Li et al. (2013), who found a positive relationship between job demands and emotional exhaustion among crude oil production workers. One definition of fatigue in the Encyclopedia and Dictionary of Medicine, Nursing, and Allied Health is "a generalized feeling of tiredness or exhaustion" (Miller & Keane, 1997, pp. 585). If the workload is excessive with long-term exposure, it may result in fatigue (Biebuyck, Weinger, & Englund, 1990). The support of *H1* is also consistent with research findings confirming the positive association between task demands and fatigue level (MacDonald, 2003; Van Yperen & Hagedoorn, 2003). A study of nurses found a strong relationship between job demands and indicators such as workload and feelings of exhaustion (Demerouti et al., 2000). In the **combined model**, task demands were measured by physiological and activity measurements, and exhaustion was measured by heart rate variability indicators. Therefore, the results show a close association between energy expenditure, relative heart rate, and heart rate variability measurements.

The results for *Hypothesis 2 (H2)* shows that an increase in personal resources is not associated with decreased exhaustion. In the combined model, the personal resources construct was measured by indicators obtained from the 12-item Short-Form Health (SF12) survey. The general health, physical functioning, and role functioning indicators in the SF12 were ultimately selected to measure the personal resources construct in the final **combined model**. There is a possibility that objectively measured heart rate recovery (i.e., a slow heart rate's return to its resting heart rate) could be an indicator that is correlated for predicting physiological fatigue, as shown by Brouha (1967). However, the heart rate recovery indicator was removed during the assessment of the measurement model due to its low reliability and convergent validity with SF12 indicators. While Kenny et al. (2008) reported that physical work ability can be measured from cardiovascular, respiratory, metabolic, and muscular functions, the final model in this research operationalized personal resources with the subjective measurement of health to meet the reliability and convergent validity requirements of the measurement model. Sleep indicators such as sleep quality, total sleep, and the sleep fragmentation index were also removed from the measurement model because of their minimal ability to explain the variation in the exhaustion construct (i.e., not improving $R^2$for the exhaustion construction). In this study, SF12 was measured before work tasks were conducted, and exhaustion was measured through heart rate variability indicators during the task. If SF12 was measured after the completion of the work, the result in this way may have revealed a correlation with exhaustion. After a certain amount of physical activity, the subjects may be able to better understand their health status. In this way, the causality of the relationship between SF12 and exhaustion may be reversed.

The support of *Hypothesis 3 (H3)* suggests that personal resources are negatively associated with the level of disengagement. This result indicates that the association between job resources and disengagement (Demerouti et al., 2000) would hold in a similar fashion at the task and individual level. In previous JD-R model studies (e.g., Demerouti et al., 2000; Bakker et al., 2004), factors such as supervisor support, feedback, participation, autonomy, and development possibilities were measured in the job-resources construct. In contrast, personal physical capability and health status were measured as personal resources for task performance in accordance with the scope and context of the current study. The current study found a relationship between disengagement and the use of personal resources among the research subjects. The hypothesized positive association between exhaustion and disengagement (*Hypothesis 4: H4*) was not statistically significant. This result is inconsistent with Bakker et al. (2004)'s findings, which showed a positive relationship between exhaustion and disengagement. The association between exhaustion and disengagement found by Matthews (2002) becomes relevant and applicable when cognitive functions play a significant role and are required. For example, the role of a truck driver requires cognitive functions that are much more taxing than the physical functions that an individual must perform when driving.

The relationship between exhaustion and productivity performance (*Hypothesis 5*a: H5*a*) is significant. Thus, it is generally known that there is a negative correlation between burnout and productivity (Golembiewski & Munzenrider, 1988). However, result of *Hypothesis 5*a* (*H5*a*) shows that a higher level of exhaustion is positively associated with increased productivity, contrary to the hypothesis of the current research. This may be because the task was limited to an hour, which allowed subjects to maintain their pace of productivity while actually being exhausted. In other words, the state of exhaustion may not have been sufficiently long to cause a decrease in productivity. The lack of support for *Hypothesis 5*b (H5*b)* indicates that there is no significant negative association between the level of exhaustion and the safety performance for an individual. This result contradicts the results of Li et al.'s (2013) study, which reveal a positive relationship between safety performance, as measured by near-misses, injuries, and emotional exhaustion. This may be because the safety indicator used in the current research was the increased risk of a musculoskeletal disorder, which is not in fact a consequence, such as with a physical injury. Also, Li et al. designed a research model with the 'emotional' dimension of exhaustion; however, the current research indicates the 'physical' dimension of exhaustion in the JD-R model. This difference may conclude the different relationship between exhaustion and the safety performance.

The test results for *Hypothesis 6*a (H6*a)* suggest that increased disengagement (i.e., decreased engagement) is associated with decreased productivity performance. In other words, as in the study of Rich et al. (2010), engaged workers use their physical, cognitive, and emotional energy more often and demonstrate higher performance. This can also explain how highly engaged workers may be eager to maintain high productivity even though they are emotionally and physically exhausted, as shown by Moeller et al. (2018)'s findings. The test for *Hypothesis 6*b (H6*b)* shows the negative relationship between disengagement and safety performance. The relationship is statistically significant, though the direction of the relationship is reversed. By contrast, Nahrgang et al. (2001) showed a positive relationship between engagement and safety performance. A potential explanation for the inconsistency in our results with those of Nahrgang et al. (2001) is that they measured engagement as safety involvement, participation, and communication, while the current research measured engagement as an individual's level of absorption and motivation for the production goal required for a task.

Earlier findings by Bakker et al. (2004) revealed that job resources have no moderating effect on the relationship between job demands and exhaustion in employees working in various sectors, such as industrial work and construction. The result of testing on *Hypothesis 2** (*H2*)* in the current research also shows that there was no moderation effect of personal resources on the relationship between task demands and exhaustion. This means that personal resources measured by subjective health status have a limited capability to buffer the impact of task demands on exhaustion. The results of this buffering effect could vary, depending on the variables that are used to for measurement and on the construction workers' type of work. In terms of the mediation effect in the proposed model, the full model analyzed only the indirect impact of task demands and personal resources on productivity and safety performances due to the limited sample size. The mediation effect of exhaustion and disengagement was analyzed after including the direct paths between task demands and performance constructs and between personal resources and performance constructs in the revised model. Then, statistically significant paths that were found in hypotheses testing in the proposed model as shown in Table 5.50 were only included for testing the mediation effect (see Figure 5.6). In the current study, it was found that safety and productivity goals could not be set in the same direction. Balance is required for both short-term labor productivity and the ergonomic safety of material-handling work. Based on the R^2 values obtained, the final model proposed in this study was able to account for 18% of the variance of the productivity performance construct, and 5% of the variance of the safety performance construct. The prediction accuracy for the productivity performance of the current research was higher than that by Bakker et al. (2004), who reported 8% variance, which explained in-role and extra-role performance. Nahrgang et al (2010)'s research showed that the percentage of variance in unsafe behavior was explained by burnout at 34.3% and engagement at 14.1%, both of which are significantly higher than the result of the current study. The low percentage of variance, which explained the outcome constructs of the current research, mainly occurred because multiple indicators used to obtain measurements through both subjective and objective methods were eliminated to ensure the measurement model could meet the reliability and validity criteria in the PLS-SEM analysis. It is still necessary to explore the theory by using objective measurements from JD-R and burnout models, as well as the constructs described by measurement variables. There is no clear distinction regarding which research constructs should be used to obtain physiological and mental measurements through various wearable sensors.

6.2 Theoretical implications

The current research contributes to developing a conceptual framework for building a productive and safe workforce and to promoting the use of wearable health-monitoring technology in the construction domain. This study examined the application of wearable sensor technology and integrated it with existing theories of JD-R, burnout, and performance (productivity and safety) at task and individual levels. The results of the current study pertain to workers with physically demanding jobs but low decision latitude. According to the classification of job quadrants introduced by Karesek and Theorell (1990), construction laborers, miners, and freight handlers belong to this group (i.e., specifically jobs with high physical exertion and low decision latitude). Mitropoulos et al. (2009) introduced variables and components that comprise task demands and capabilities in the concept of the task-capability interface (TCI) model. Task demands rely on task factors, environmental factors, and work behavior. Each element also contains many measurable parameters (Mitropoulos et al., 2009). For instance, the task factor is influenced by the tools that the worker uses, the material weight, the distance of handling the material from the inventory area to the working area, and so forth (Mitropoulos et al., 2009). Capability is determined by the worker's overall competency, attention level, and human factors (Mitropoulos et al., 2009). In the current study, capability was measured by the physical ability to conduct material handling that meets the unit of analysis and scope of study. This research design might have impacted the eventual research findings, which confirm that increased exhaustion is not positively associated with a decrease in productivity, as hypothesized. This may be because the time given for the task to be performed during the experiment was 1 hour. If the work was carried out for 8 to10 hours, which is the actual duration of working hours for construction workers, the increase in exhaustion could lead to a decrease in productivity.

According to Yerkes and Dodson (1908), a certain level of demand is needed for effective performance. However, when acceptable demands exceed a peak level, performance begins to decline. That is, there is a parabolic (i.e., invert U) relationship between performance and demands. This non-linear relationship between productivity and task demands could partially explain the low level of predictive accuracy of productivity performance since the current research assumed a linear relationship between these factors in the proposed model. Furthermore, the current research shows that exhaustion has a full mediation effect on the relationship between tasks demands and productivity performance. Therefore, any approach seeking to understand the direct relationship between task demands and productivity without the exhaustion construct would not inappropriate. Selye (1978) stated that there are two opposing occupational stresses: positive stress (Eustress), and negative stress (Distress). Positive stress may account for a highly engaged, exhausted worker's high productivity.

In general, unsafe incidents are known to occur due to workers' lack of attention, negligence, carelessness, and ignorance when working (Hinze & Parker, 1978). However, in the current study, subjects with high task engagement were found to perform material-handling tasks in a more unsafe manner in term of ergonomics posture in order to increase output. The subjects knew the nature of ergonomically safe posture in material handling, as all subjects were trained by watching an ergonomics safety video and tried the safe lifting posture a couple of times before conducting work sessions (see experiment procedure in Figure 3.10). The findings from the current research on the effect of exhaustion and engagement on productivity and safety outcomes are in line with

Herzberg's motivation-hygiene theory (Herzberg, 2005). Herzberg (2005) showed that there are two heterogeneous desires in humans regarding hygiene and motivation factors. Herzberg stated that the hygiene factors include safety, money, status, interpersonal relationships, and working conditions. These factors are related to the working environment and the conditions under which the work is done (Herzberg, 2005). Motivation, on the other hand, is a factor that brings satisfaction, such as recognition and a sense of accomplishment, which affects the increase in individual productivity (Herzberg, 2005). Herzberg also found that the need for a motivational factor arises when the desire for hygiene is satisfied. Therefore, in the current study, subjects who thought that material handling would affect their safety adversely (i.e., eventually high safety performance) may have tended to show lower engagement while working. In other words, because the desire for hygiene factors was not met, engagement may have declined, and productivity performance may have been lower. Consequently, performance was lower because it was prioritized as a function of safety (i.e., hygiene) rather than as a function of workers' motivation related to material handling.

The data analysis results of the current study also show that subjects will not achieve both productivity and safety at the same highest levels. Thus, the optimal level of task demands and personal resources need to be planned to achieve both productivity and safety performance goals. These findings can be explained based on Maslow's hierarchy of needs (Gawel, 1997). According to Maslow's theory, safety is a basic need that must be met prior to higher-order needs such as self-actualization or self-esteem (Kroemer, 2017). These theories can explain this study's finding that a higher level of disengagement with a lower level of exhaustion is related to a higher level of safety performance. In addition, according to Maslow's hierarchy of needs, the desire for safety must be prioritized first, and the desire for achievement, second (Gawel, 1997). Thus, if a lack of safety is expected, the subject can be demotivated by the work (Parkin, Tutesigensi, & Büyükalp, 2009).

According to Nahrgang et al.'s (2001) research, higher engagement levels are associated with increased safety performance. However, according to the data analysis results in the current research, material-handling tasks for entry-level construction workers indicated that high engagement at work has a less positive impact on safety. Moeller et al. (2018) specified that such workers are represented as engaged-exhausted groups. Therefore, to prevent burnout among engaged workers and maintain high production goals among them, it is necessary to detect when workers in the engaged-exhausted group are experiencing burnout early. Hence, the use of wearable technology can be beneficial for the early detection of workers' excessive levels of exhaustion. For construction material handling, a worker who is doing an excellent job is also prone to be a risk-taker. Levitt and Samelson (1987) noted that very safe crews monitor each other as a form of awareness, aim to prevent immediate risky behavior in risk takers, and explain the remedies for risky behaviors among workers (Levitt & Samelson, 1987). As such, the management of high-performing workers and risk takers is separate, and the two groups have been recognized as being different.

There are two controversies regarding the most effective approach for managing workforce burnout, namely, the individual approach and the organizational approach (Schaufeli et al., 1993). The current research supports the individual approach, considering that workers' burnout status could vary daily and even weekly. Reason (2000) noted that several human errors have been caused by the best workers. Based on the proposed model of the current research, the findings can explain why the best workers performed at a high level of productivity with a lower level of safety performance.

6.3 Managerial implications

The online JD-R tool introduced by Schaufeli (2017) can be implemented for frontline construction workers' management by safety professionals and managers. However, it is necessary to modify the context of the online tool for its application in the task and individual levels of JD-R and the monitoring of burnout. Workload and production pressure, which exceed a worker's capacity, negatively influence a worker's behavior. Therefore, a planning production process that considers workers' capabilities is important for improving their safety and productivity. This finding provides empirical evidence supporting Lingard (2003), who suggests that job characteristics are more important predictors of burnout than demographic characteristics or personality traits. Lingard recommended that the preferred preventative strategy is to redesign the jobs of engineers. Workers exposed to monotonous and repetitive tasks become increasingly proficient in such tasks and perform them at an increasingly faster rate (Kroemer, 2017). However, this varies from person to person, as workers bored by the repetitive work may, in turn, reduce production due to decreased motivation (Kromer, 2017). Thus, the monitoring of job demand-resources and burnout is necessary on a daily basis. Previous research by Lee and Migliaccio (2016) revealed that both daily and weekly variations exist in task demands, as shown by the measurement of heart rate. Additionally, burnout (as measured by exhaustion and disengagement) may also show daily variations (Sonnentag et al., 2010).

The advantages and disadvantages of using surveys, observations, and direct measurements of human factors have been investigated, and their correlations with one another have been assessed (Barriera-Viruet et al., 2006; Spielholz et al., 2001). As there are both advantages and disadvantages to direct measurement using wearable technology, it is still too early to determine whether this method is superior to survey measurement. Regarding the measurement of the safety performance construct, ergonomic safety behavior was quantified by the ratio of the time spent in the non-neutral flex posture to the time spent in the neutral sagittal-bending posture. In this research, ergonomic safety is a metric that quantifies the amount of time spent by a worker while being extended beyond the threshold trunk angle. This metric is suitable for comparing individual workers' exposure to ergonomic hazards. In addition, using this measure as an index of safety and as an indicator of productivity allows an analysis of safety for workers who are less engaged in work and for those who engage in relatively few lifting and lowering activities. Therefore, this is an appropriate method for quantifying the frequency of exceeding the trunk-bending threshold in each lifting operation. Productivity is commonly expressed as an equation 6.1 (Liou & Borcherding, 1986).

$$\text{Productivity} = \frac{\text{Output}}{\text{Inputs}} \tag{6.1}$$

There is a way to reduce the time wasted during the installation of one unit of material to, in turn, reduce the time used for production. However, an extensive review of studies conducted by Koukoulaki (2014) has shown that this approach increases repetitive work, which can increase ergonomic risk exposure. Therefore, in material-handling activities, it is necessary to improve productivity by increasing output by work (or workplace) redesign and worker's skill training rather than by minimizing the input through the increase of the workpace.

As Kroemer (2017) noted, it is impossible to measure an individual's physical and mental responses with only a few physiological techniques; it should also be noted that there are differences between objective measures and subjective judgments. Therefore, using multiple sample methods and understanding the advantages and disadvantages of each are necessary to predict the performance of a JD-R model for construction workers. The current study also provides a preliminary finding regarding the physiological monitoring of the workforce in the context of lean construction principles, especially with regard to repetitive motions. Conti, Angelis, Cooper, Faragher, & Gill (2006) found a potential controversy in the implementation of lean principles in material handling, as such principles can increase the frequency of work activities and thus potentially increase the risk of ergonomic hazards.

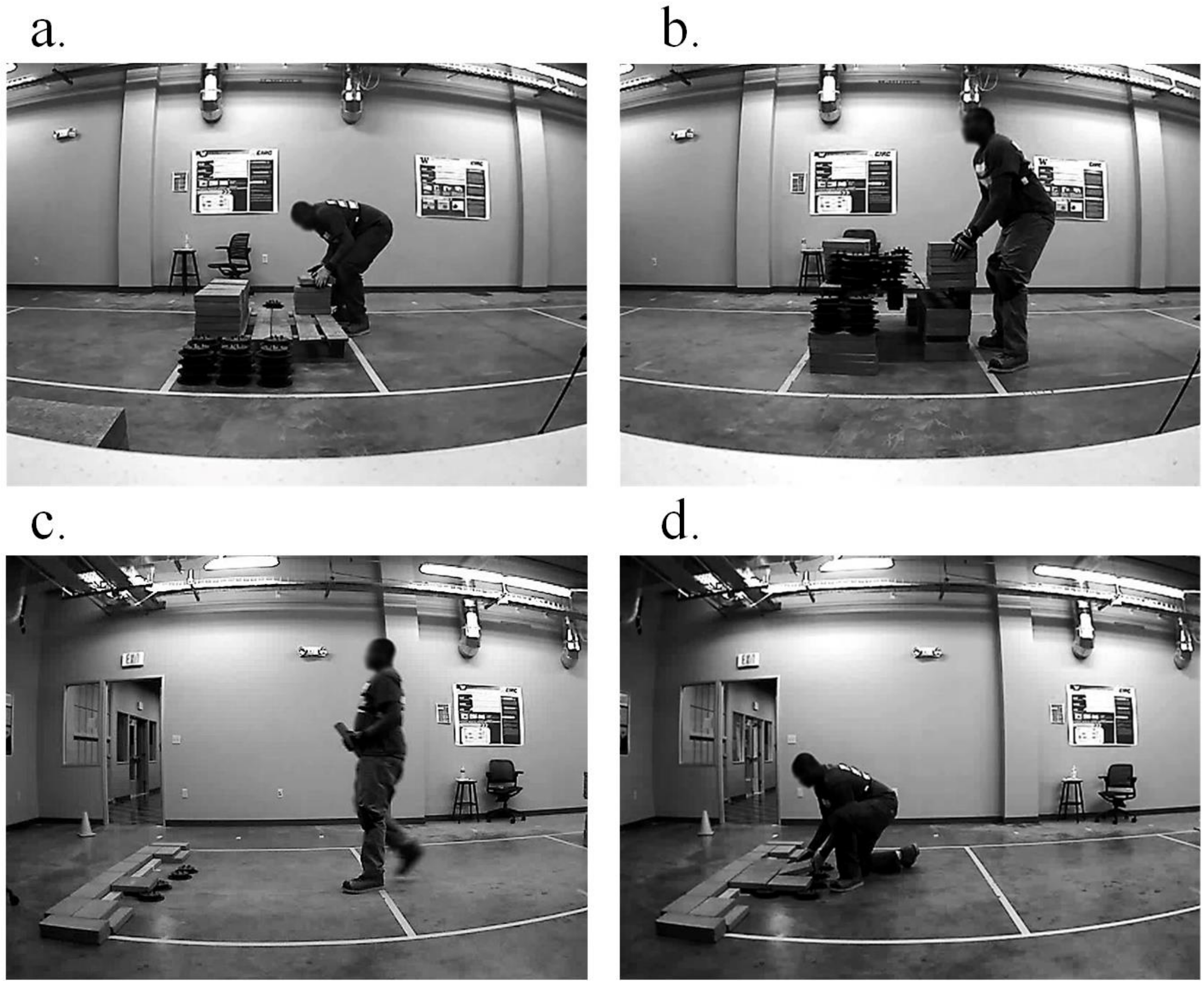

Figure 6.1 Example of work tasks

Figure 6.1 (a) shows the lower part of the platform in the material area; the subject's workload is designed to be more strenuous than that which is shown in Figure 6.1 (b), which shows a subject lifting a paver onto a raised material pallet closer to subject's knuckle height. The strenuous workload is associated with a higher level of exhaustion. To prevent workers from taking on excessive workloads in material handling jobs, safety professional guidelines limit the weight of materials that workers need to install and carry. In terms of ergonomics, it is better to manage the demands of all tasks through the control of tools, equipment, and the work environment. If possible, the safety professional, designer, engineer, owner, and manager should effectively communicate to select appropriate materials in the early construction project phase and to plan and store inventory during the construction phase. If the repetition of material handling activities is necessary for a worker, materials should be placed closer to him or her at a convenient height rather than on the ground. As Reason (2000) noted, the individual worker's capability cannot change within a short period of time, while a short-term change or immediate control of demand is possible through intervention during the project. Therefore, managers need to implement production control focused on methods for controlling and minimizing the chances of over-demand on laborers. According to the Yerkes-Dodson law (Yerkes &Dodson, 1908), the relationship between the stress level and performance is demonstrated by an inverted U-shaped rather than a linear relationship (Teigen, 1994). That is, medium-level stress helps to produce the best performance. If the intensity of a given task is sufficiently high to cause burnout, it will degrade performance; however, workers' performance will also be low if the stress level is too low owing to tedious work. Monotony in work tasks increases the likelihood of burnout (Kroemer, 2017). Therefore, planning to create diversity in work tasks would be beneficial.

The global market for wearable technology is growing quickly, and the McKinsey Global Institute reported that wearable computers for the monitoring of human health is a promising business trend that promotes the "quantified self" movement and people's well-being (Bughin, Chui, & Manyika, 2013). Construction workers face physiologically and psychologically rigorous demands at their job sites, where they are also exposed to severe outdoor environments. Based on the fast growth of this business sector, small-sized wearable technologies, such as heart-rate monitors, activity trackers, and electroencephalograms, can be distributed at reasonable prices now or in the near future.

Wearable technology can help safety professionals come to better-informed decisions, but it is not a substitute for safety professionals in itself, as Schall (2017) has noted. It is important to predict safety and productivity through wearable sensors and survey measurements using the proposed JD-R and burnout models and to show the positive benefit outcomes over costs in construction organizations. However, a barrier to adopt wearable technologies in field management has been discussed by safety professionals. For example, Schall, Sesek, and Cavuoto (2018) noted through a survey of safety professionals that the problems of privacy, confidentiality, employee compliance, and sensor durability are the potential issues for the application of wearable technologies.

6.4 Research implications

Subjects' trunk flexion was measured using the accelerometers in Zephyr^{TM} physiological status monitors; this device was used to determine subjects' ergonomic hazard level based on how far the joint angle near the lumbar area exceeded the given threshold. However, studies using accelerometers or the inertial measurement unit (IMU) have limitations when measuring another element of ergonomics safety—asymmetry during lifting. Thus, in this study, this was measured through video analysis. However, this method's use at the construction site is constrained to the present (Lu, Waters, & Werren, 2015). Posture asymmetry affects the back's compressive force and the total moment by changing the direction and magnitude of the force when lifting material of the same weight (Pope, Goh, & Magnusson, 2002). Therefore, a thorough analysis of posture required additional analysis with a focus on lateral bending and twisting while lifting and lowering material. The positioning of the hands and arms when lifting heavy material was also critical to the level of compression forces on the lumbar vertebrae area.

One remarkable characteristic of emerging wearable-sensor technologies is their function of collecting multiple parameters, thus allowing for multisource data collection. The multi-parameter monitoring involves wearable sensors that comprises composite physiological-status monitors, as well as activity and motion sensors. Occupational and environmental exposures at construction sites are often multifactorial and thus require multiple measurements. A holistic dataset can be provided by the composite sensors, unlike the type of sensor that collects only a single parameter. Off-the-shelf composite sensor systems are commercially available, and they have been used in various academic studies in occupational safety and health research. Introducing a methodology for collecting data by applying mixed methods to a physician's clinical activities, Calvitti et al. (2017) explained how to integrate the methodologies of a time-motion study that were introduced both before and after obtaining multisource data in a clinical setting and then applied this method to actual test beds.

Since the subject is aware of being monitored by the camera, the subject may continue to consume energy for production despite increased exhaustion. Regarding this factor, privacy affects the application of a wearable sensor (Schall et al., 2018). Judgment of a production record from a first-person viewpoint, such as using a camera clip (Piwek, Ellis, Andrews, & Joinson, 2016), is needed more than behavioral observation through a camera from a third-person perspective. Sometimes, reliable data cannot be collected, and the data analysis investigates the relationship between latent variables that can be biased due to the Hawthorne effect (Stanton, 2004). Efforts to minimize this effect should be carefully applied for any study in this field. An intensive literature review, consultations with occupational safety, health, and sports medicine professionals, and additional experiments with students in a laboratory setting are necessary to validate the issues above. While the current study was conducted in a laboratory setting, naturalistic viewpoints are also necessary. In a natural work environment, controlling confounding etiological agents is very important for the association analysis of research constructs. This is the main reason for choosing a laboratory setting for the experimental design of this study. Heat in outdoor conditions will be a factor for task demands, which will eventually influence workers' productivity (Yi and Chan, 2017).

6.5 Limitations and future research

Because the research in this this dissertation was conducted as a cross-sectional design study, the causal relationship, including directionality, cannot be clearly defined regarding the association between the two research constructs. However, according to a previous study conducted by Lee and Migliaccio (forthcoming), there was no clear time-lagging effect between the two variables when considering the effects of task demands on productivity. Therefore, it is possible to predict performance outcomes by using the JD-R model, assuming that task demand measured at one point in time can predict the measured productivity at the same time. The findings of the current research are applicable to construction trade workers who are extensively involved in manual material-handling activities, such as placing and removing a raised deck, flooring, and masonry. Further investigation needs to be conducted to test the hypothesis model on construction activities that are ordinarily encountered in routine repetitive motions, such as tying rebar, erecting steel, assembling formwork, and framing wood. As the study's unit of analysis is assigning a simulated task in a controlled environment, the original burnout survey instrument was replaced with the most applicable available questionnaire to more effectively measure the latent variable. Following the IRB protocol, all the subjects recruited were trained on the ergonomic safety of lifting and lowering materials by watching a video tutorial from an organization that is certified to create the training video. The personal difference regarding the educational retention or better/worse understanding of the training could influence on the safety performance outcome (i.e., ergonomics safety behavior) in the research model.

The magnitude of task demands that an individual can accept depends on physical capacity. A limitation exists in using physical ability through SWMT as a predictor of workers' response to the demand of construction tasks. The current research measured performance by using the dual dimensions of productivity and safety. However, as Kroemer (2017) has mentioned, this type of testing has the limitation of testing the capabilities of the lower body only, without examining trunk and arm capabilities. Future research should include the testing of several other physical conditions that are directly related to material-handling activities, such as timed up and go (TUG) and lift and carry tests, in order to assess subjects' physical capability for installing the raised decks to be assessed with greater precision. Quality can be an additional factor of performance in the proposed research model. Job competition, an important social factor, not only increases the risk of injuries but also reduces the quality of work and increases rework (Hinze & Parker, 1978). The quality of work was visually assessed by the researcher, and the subject received instructions and feedback to maintain an acceptable level of performance. In all subjects and experiment sessions, quality was maintained at an acceptable level. However, there is a possibility that the process of instruction and surveillance on the quality affected the subject's safety behavior or productivity level. Thus, it is necessary to quantify the task quality and to control the task quality as an experimental variable.

Reason (2000) stressed the importance of the system approach to explore how changing working conditions can affect the variability of issues that may lead to human errors, where workers' awareness cannot change their work conditions. The system approach acknowledges that errors can always occur in relation to workers and that this system trains them to handle mistakes. As Reason (2000) noted, changing work conditions may be one approach to minimize accidents in a short-time period compared with making efforts to change the human behavior. However, a long-term approach to achieving high reliability within an organization, including an effort to understand, conduct trainings, and educate people, could be more reliable and might also need to be implemented. Thus, understanding both individual and organizational levels are equally important for the management of human error. Therefore, further research should investigate the adaptation of a JD-R model in an organization and test models by using organizational data.

In the current research, electroencephalography (EEG) could not be applied to experiments owing to budget limitations. EEG can objectively measure workload and task engagement, which is the construct of the current research model. Abrantes, Comitz, Mosaly, and Mazur (2017) measured the cognitive workload of physicians more objectively by using an EEG sensor. They also introduced a prediction model of workload by using a machine learning model. EEG has the advantage of predicting physicians' workload in real time. In Calvitti's (2017) study, the activity of physicians was a continuous variable, whereas task load was evaluated after patient visits. Therefore, to sufficiently utilize continuous variable data, the workload should be continuously measured by using EEG. Potentially, the recorded video (originally used for performance measurement in the current study) during the experiment can be observed by multiple raters, and the subject's engagement on task can be coded. Kolanowski, Buettner, Litaker, and Yu (2006) obtained nurse practitioners' activity engagement from video recordings in their study and blinded the condition and hypothesis of study from the video raters.

Because the age group was limited to young entry-level workers, the outcome of this research can be similarly applied to aged workers on a limited basis. The study assumed that trainees in a pre-apprenticeship program and university students were in one homogeneous group. As described in Tables B.1 through B.5 in Appendix B, the mean values for some parts of the measurement variables were similar for the two groups; however, the mean values for other parts of the variables were remarkably different between the two groups. Further research is needed to understand how task demands and personal resources affect exhaustion and disengagement and how the relationship between safety and productivity performance ultimately varies between groups. There is a need to validate the idea that wearable sensors that take physiological measurements are the most effective parameters for enabling the real-time gauging of workers' overexertion, task demands, and personal resources.

Chapter 7 Conclusions

Workers in the affordable, human-built construction industry have suffered from stagnant labor performance, hazardous working environments, and health risks. The construction industry has a high rate of occupational fatalities and injuries. Ongoing and impending retirements are leading to a shortage of skilled and experienced workers in the construction industry. The industry is also struggling to attract new young workers and mitigate its high turnover rates. The dominant organizational culture of primarily emphasizing results over means often exposes workers to risks that increase the rate of accidents and injuries. Hence, human resource management in construction is crucial to ensure full capacity utilization in optimal work environments and healthy work conditions. The current study investigates the adoption of sustainable workforce management in construction, based on an understanding of the factors that influence workers' burnout and unsafe ergonomics behavior, as well as their productivity performance.

This dissertation research aimed to investigate the manner in which data from physiological status monitoring can be utilized in production planning (at the task level) to improve safety without a critical loss in productivity. A few studies, including Sonnentag's (2017), investigated the concepts of daily JD-R and burnout at the task level. In construction management, productivity and safety performance are important indicators of project success. However, exploratory studies of models that predict performance indicators through the JD-R model have rarely been performed. This dissertation study also takes an existing descriptive case studies (e.g., Lee & Migliaccio, 2014, 2016) and applies an explanatory method to empirically determine variations in task demands by measuring heart rate during manual handling activities, and employing partial least squares structural equation modeling and sequential hypothesis testing. Job demands and resources have been evaluated only by undertaking subjective measurements using survey instruments. This current study found that combed model with survey (i.e., subjective measurement) and sensor measurements (i.e., objective measurements) increases the predictive power of the outcome construct of a model, in comparison with a model whose predictive accuracy depends solely on surveyed measurements. Schaufeli et al. (1993) emphasized the importance of continuous research on different assessment methods, including the use of physiological assessments in burnout studies. Explanatory research is needed on applying new measurement methods to the burnout model for the development of wearable technology, in addition to active research on occupational stress measurements.

With the recent developments in wearable sensors, such as physiological status monitors and activity trackers, indicators for measuring physical job demands can be more objective than traditional subjective surveys. This study promotes research in the construction engineering and management domain to understand JD-R, burnout, and performance and uses PLS-SEM to determine individual, team, and organizational behaviors for improving productivity and safety. Theoretical and practical explanatory research using physiological variables of the JD-R model has time-related constraints regarding data collection. This study investigates how wearable sensor data can predict exhaustion, disengagement, and performances so that managers can optimize the production process based on objectively measured human resources data. Despite efforts by academia and industry, there still exist barriers to the use of wearable technologies at worksites. There are many silos related to connectivity among wearable technologies, and a need for strong agreements and policies on the personnel who will access and manage the data to protect privacy. An important consideration is how the data can be used for managerial applications, and how and where data collected by wearable technologies can be employed. Most of the data used has limitations in terms of detecting or controlling abnormal human behavior or environmental conditions in the field (Manyika et al., 2015). Construction workforce management should monitor employee needs in collaboration with frontline managers by using objective data from wearable technologies.

To prevent workers from taking on excessive task demands in material handling activities, safety guidelines limit the weight of materials that workers need to install and carry. Continuous training programs should be planned for workers, including instruction on the proper posture for lifting material. Due to the limitation of the sample size, the proposed model consists of indirect paths from task demands and personal resources to performance outcomes, and hypothesis testing is performed by applying PLS-SEM. The mediation effect of exhaustion and disengagement was analyzed after including the direct path in the revised model, and utilizing only the significant paths among the indirect paths from task demands and personal resources to performance outcomes. Exhaustion has a fully mediating effect on the relationship between task demands and productivity. Therefore, the emotional and physical exhaustion of workers is crucially linked to their productivity when performing physically demanding work. Disengagement was found to have no mediating effect on the relationship between personal resources and productivity. However, this study shows that disengagement partially mediated the relationship between personal resources and productivity. The higher the personal resources, the higher the productivity (from both total effect and indirect effect).

Daily burnout and production reliability should be incorporated into the JD-R model to predict safety and productivity outcomes. Engagement can be transferred among people through the crossover process; therefore, a positive engagement mood can lead to an overall improvement in task performance (Bakker & Leiter, 2010). A limitation of this study is that it does not consider the influence of such interactions between people. Bakker and Leiter (2010) found that subjectively reported health, used as a measurement to operationalize personal resources, was associated with engagement. However, there was no relationship between exhaustion and operationalized physiological measurements and engagement based on the findings of the current research. The current study found safety performance to be negatively correlated with high engagement, which potentially indicates over-engagement. A Seppala and Moeller (2018) emphasized, human-resource management requires paying attention to highly engaged but burned-out employees so as to keep them working and help them contribute to organizational goals. Safety professionals can incorporate the JD-R and burnout model in the continuous improvement process to control related risk factors and the cause of musculoskeletal disorders. Engineers, owners, and managers should communicate efficiently to balance productivity and safety by modifying work layouts, tools, and equipment (Rostykus & Barker, 2018). Selection of appropriate materials and the planning and storage of inventory should be evaluated for cost effectiveness, risk minimization of musculoskeletal disorders, and maximization of frontline workers' productivity. Although there are limitations, this study is significant because it examines the job characteristics affecting construction workers' performance. It unveils the "black box" mechanism of the association between job characteristics and performance using burnout theory in the task level. In contrast with existing research, this study measures the unique characteristics of construction performance by considering two dimensions—productivity and safety. Finally, this study contributes to the application of emerging wearable sensor technology in construction management research.

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Appendix A: Description of measurement variables

Table A.1 Descriptions of measurement variables (Task demands construct)

Latent Construct	Measurement Variable name	Description of measurement variables	Unit of measurement variables	References
Task Demands (TD)	td_Hrbpm (td1)	Average heart rate during the task	Beat per minute (bpm)	Å strand (1960); Abdelhamid & Everett (1999)
	td_Enerkcal (td2)	Total energy expenditure measured via ActiGraph worn on waist	Kcal	ActiGraph (2016d); Freedson et al. (1998); Swartz et al. (2000); Williams (1998)
	td_Enermet (td3)	Total energy expenditure via ActiGraph worn on waist	MET	
	td_Wenerkcal (td4)	Total energy expenditure measured via ActiGraph worn on wrist	Kcal	
	td_Wenermet (td5)	Total energy expenditure measured via ActiGraph worn on wrist	MET	
	td_ Percworkload (td6)	Perceived workload measured by NASA TLX, scored by weighted method	none	Mitropoulos & Memarian (2013); Mehta & Agnew (2011)
	td_Rtlx (td7)	Perceived workload measured by NASA TLX, scored without weighting (i.e., raw NASA TLX)	none	
	td_Physicald (td8)	Subscale of NASA TLX for physical demand	none	
	td_Temporald (td9)	Subscale of NASA TLX for temporal demand	none	
	td_Mentald (td10)	Subscale of NASA TLX for mental demand	none	
	td_Effort (td11)	Subscale of NASA TLX for effort	none	
	td_Frustrationl (td12)	Subscale of NASA TLX for frustration level	none	
	td_Inversedp (td13)	Inversed scale of NASA TLX performance.	none	
	td_Rhr (td14)	Relative heart rate: Normalized heart rate unit based on resting heart rate and maximum heart rate.	percentage	Kirk & Sullman (2001); Rodahl (1989); Wu & Wang (2002)

Table A.2 Descriptions of measurement variables (Personal resources construct)

Latent Construct	Measurement Variable name	Description of measurement variables	Unit of measurement variables	References
Personal Resources (PR)	pr_Resthr (pr1)	Resting heart rate measured during 10 minutes before conducting material installation task	bpm	Ståhle et al. (1999)
	pr_Smwt (pr2)	Six-minute walk test conducted on 15-meter track	centimeters	Pepera et al. (2012)
	pr_Hrr (pr3)	Heart rate recovery that measures the heart rate difference between peak measurement at the end of a task and released heart rate 2 minutes after the task completion	bpm	Kokkinos et al. (2012)
	pr_Sf12pcs (pr4)	The 12-item Short Form Health Survey (SF12) physical component summary including measurement items general health (GH), physical functioning (PF), role physical (RP), bodily pain (BP)	none	Larson (2002); Lim & Fisher (1999)
	pr_Pfnbs (pr5)	Subscale of SF12 physical health for physical functioning	none	
	pr_Rpnbs (pr6)	Subscale of SF12 physical health for role physical	none	
	pr_Bpnbs (pr7)	Subscale of SF12 physical health for bodily pain	none	
	pr_Ghnbs (pr8)	Subscale of SF12 physical health for general health	none	
	pr_Sleepqual (pr9)	The sleep efficiency measured from total sleep time divided by the total amount of time the subject was in bed	percentage	Cole et al. (1992); Tudor-Locke et al. (2013); ActiGraph (2012); ActiGraph (2018)
	pr_Totalsleep (pr10)	Total number of minutes that the sleep algorithm scores the subject's data as "asleep"	minutes	
	pr_invSfi (pr11)	Sleep fragmentation index(SFI) that measured restlessness during sleep (unit in percentage). A higher SFI indicates that the subject's sleep was more disrupted. pr_invSfi is an inverse value of SFI.	none	

Table A.3 Descriptions of measurement variables (Exhaustion construct)

Latent Construct	Measurement Variable name	Description of measurement variables	Unit of measurement variables	References
Exhaustion (EX)	eh_Cis (eh1)	Total score of the Checklist Individual Strength (CIS) survey	none	Beurskens et al. (2000); Hewlett et al. (2011)
	eh_cisitem1 (eh2)	Subscale of CIS survey for “I feel tired” item	none	
	eh_cisitem2 (eh3)	Subscale of CIS survey for “Physically I feel exhausted” item	none	
	eh_cisitem3 (eh4)	Subscale of CIS survey for “I feel fit” item (inversely scored)	none	
	eh_cisitem4 (eh5)	Subscale of CIS survey for “I feel weak” item	none	
	eh_cisitem5 (eh6)	Subscale of CIS survey for “I feel rested” item (inversely scored)	none	
	eh_cisitem6 (eh7)	Subscale of CIS survey for “Physically I feel I am in a bad condition” item	none	
	eh_cisitem7 (eh8)	Subscale of CIS survey for “I get tired very quickly” item	none	
	eh_cisitem8 (eh9)	Subscale of CIS survey for “Physically I feel in a good shape” item (inversely scored)	none	
	eh_Sdnn (eh10)	Heart rate variability time domain measure: Standard deviation of all NN intervals	ms	Camm et al. (1996); Tarvainen et al. (2014)
	eh_Rmssd (eh11)	Heart rate variability time domain measure: The square root of the mean of the sum of the squares of the differences between adjacent NN intervals	ms	
	eh_Hrvlffft (eh12)	Heart rate variability frequency domain measure: Power in low frequency range between 0.04 and 0.15Hz	ms^2	
	eh_Hrvhffft (eh13)	Heart rate variability frequency domain measure: Power in high frequency range between 0.15 and 0.4 Hz	ms^2	
	eh_Hrvlfhffft (eh14)	Heart rate variability frequency domain measure: Ratio LF(ms2)/HF(ms2)	none	
	eh_Hrvlffftnu (eh15)	Heart rate variability frequency domain measure: LF power in normalized unit	n.u.	
	eh_Hrvhffftnu (eh16)	Heart rate variability frequency domain measure: HF power in normalized unit	n.u.	

Table A.4 Descriptions of measurement variables (Disengagement construct)

Latent Construct	Measurement Variable name	Description of measurement variables	Unit of measurement variables	References
Disengagement (DE)	de_Sssq (de1)	Total score of Short Stress State Questionnaire (SSSQ) survey	none	Matthews et al. (1999, 2002, 2013)
	de_invitem2 (de2)	Short Stress State Questionnaire item 2: Alert	none	
	de_invitem5 (de3)	Short Stress State Questionnaire item 5: Active	none	
	de_invitem11 (de4)	Short Stress State Questionnaire item 11: "I was committed to attaining my performance goals."	none	
	de_invitem12 (de5)	Short Stress State Questionnaire item 12: "I wanted to succeed on the task."	none	
	de_invitem13 (de6)	Short Stress State Questionnaire item 13: "I was motivated to do the task."	none	
	de_invitem17 (de7)	Short Stress State Questionnaire item 17: "I felt confident about my abilities."	none	
	de_invitem21 (de8)	Short Stress State Questionnaire item 21: "I performed proficiently on this task."	none	
	de_invitem22 (de9)	Short Stress State Questionnaire item 22: "Generally, I felt in control of things."	none	

Table A.5 Descriptions of measurement variables (Performance construct)

Latent Construct	Measurement Variable name	Description of measurement variables	Unit of measurement variables	References
Performance (PR)	pf_Productivity (pf1)	Labor productivity measurement by the output per work-hour	Output/Work-hour	Liou & Borcherding, 1986
	pf_Ergo60 (pf2)	An index of improper lifting technique: Percentage of time spent with torso flexion larger than or equal to 60 degrees during 1 hour of task performance	Percentage	McAtamney & Corlett (1993)
	pf_ErgoRatio60 (pf3)	Inversed scale of relative risk: Ratio of neutral posture (i.e., percentage of time spent with torso flexion less than 60 degrees) to non-neutral posture (i.e., pf_Ergo60) that penalized the time in a neutral posture by the time in a non-neutral posture	none	Sistrom & Garvan (2004)

Appendix B: Summary of descriptive statistics

Table B.1 Descriptive statistics of measurement variables for task demands construct

	Trainee in Pre-apprenticeship program (n=10)		University Student (n=70)	
	Mean	Standard Deviation	Mean	Standard Deviation
td_Hrbpm	115.4	21.76	113.5	18.74
td_Rhr	37.4	15.85	36.1	14.10
td_Enerkcal	268.1	68.79	173.5	81.64
td_Enermet	3.6	0.45	3.6	0.67
td_Wenerkcal	274.6	58.19	141.6	50.60
td_Wenermet	3.6	0.17	3.5	0.23
td_Rtlx	8.1	1.83	9.3	2.60
td_Physicald	9.8	4.21	12.1	4.76
td_Temporald	6.2	3.97	8.0	4.65
td_Mentald	3.5	1.96	5.0	3.85
td_Effort	8.3	4.57	10.8	4.40
td_Frustrationl	2.9	3.73	5.2	4.70
td_Inversedp	17.7	4.40	14.5	4.69

Table B.2 Descriptive statistics of measurement variables for personal resources construct

	Trainee in Pre-apprenticeship program (n=10)		University Student (n=70)	
	Mean	Standard Deviation	Mean	Standard Deviation
pr_Resthr	70.7	11.86	70.0	11.48
pr_Smwt	559.4	33.91	531.3	42.23
pr_Hrr	16.4	10.43	17.7	12.08
pr_Sf12pcs	56.8	4.36	55.7	4.79
pr_Sf12mcs	54.7	1.83	50.9	8.02
pr_Sf12tot	55.8	2.09	53.3	4.29
pr_Pfnbs	56.5	2.50	55.4	4.49
pr_Rpnbs	55.4	4.07	52.9	5.10
pr_Bpnbs	53.2	4.91	52.9	8.02
pr_Ghnbs	60.7	9.22	56.5	5.96
pr_Sleepqual	78.7	7.24	84.1	6.21
pr_Totalsleep	299.1	42.91	346.0	102.08
pr_Sfi	32.5	14.21	27.8	11.50

Table B.3 Descriptive statistics of measurement variables for exhaustion construct

	Trainee in Pre-apprenticeship program (n=10)		University Student (n=70)	
	Mean	Standard Deviation	Mean	Standard Deviation
eh_Cis	19.9	5.02	24.0	6.85
eh_cisitem1	4.1	1.91	4.0	1.81
eh_cisitem2	3.7	2.45	3.8	1.72
eh_cisitem3	1.5	1.08	3.1	1.57
eh_cisitem4	1.2	0.42	2.2	1.35
eh_cisitem5	5.0	1.94	4.5	1.61
eh_cisitem6	1.3	0.67	1.8	1.08
eh_cisitem7	1.4	0.70	2.1	1.03
eh_cisitem8	1.7	1.57	2.4	1.11
eh_Sdnn	55.4	19.82	44.5	21.18
eh_Rmssd	25.7	10.48	20.9	10.80
eh_Hrvlffft	2664.3	1951.59	2159.7	2140.23
eh_Hrvlfhffft	13.9	14.39	12.7	9.20
eh_Hrvlffftnu	83.4	13.06	86.6	8.41
eh_Hrvhffft	498.7	450.31	413.5	687.86
eh_Hrvhffftnu	16.6	13.01	13.3	8.36

Table B.4 Descriptive statistics of measurement variables for disengagement construct

	Trainee in Pre-apprenticeship program (n=10)		University Student (n=70)	
	Mean	Standard Deviation	Mean	Standard Deviation
de_Sssq	4.5	0.54	3.6	0.64
de_invitem2	2.2	1.23	3.8	1.27
de_invitem5	1.5	0.71	2.5	1.21
de_invitem11	1.6	0.84	2.3	1.03
de_invitem12	1.3	0.48	2.0	0.93
de_invitem13	1.2	0.42	2.3	0.89
de_invitem17	1.4	0.70	2.1	0.74
de_invitem21	1.7	0.82	2.3	0.81
de_invitem22	1.5	0.71	2.2	0.90

Table B.5 Descriptive statistics of measurement variables for performance construct

	Trainee in Pre-apprenticeship program (n=10)		University Student (n=70)	
	Mean	Standard Deviation	Mean	Standard Deviation
pf_Productivity	133.8	19.77	142.2	38.67
pf_Ergo60	16.6	9.95	26.1	18.66
pf_ErgoRatio60	7.1	4.4	7.7	11.2

Appendix C: Survey Instruments

Physical Activity Readiness Questionnaire (PAR-Q)

Demographic Information

Participant Code:_____________

Date of Birth (YY/MM/DD):__________/______/______

Height:_______Feet__________Inches______________(cm)

Weight: _______________Pounds (Kg)

Dominant Hand: ☐ Right ☐ Left

Being physically active is very safe for most people. Some people, however, should check with their doctors before they increase their current level of activity. The PAR-Q has been designed to identify the small number of adults for whom physical activity may be inappropriate or those who should have medical advice concerning the type of activity most suitable for them

Answer yes or no to the following questions

Question		
1. Has your doctor ever said that you have a heart condition and that you should only do physical activity recommended by a doctor?	☐Yes	☐No
2. Do you feel pain in your chest when you do physical activity?	☐Yes	☐No
3. In the past month, have you had chest pain when you were not doing physical activity?	☐Yes	☐No
4. Do you lose your balance because of dizziness or do you ever lose consciousness?	☐Yes	☐No
5. Do you have a bone or joint problem (for example, back, knee or hip) that could be made worse by a change in you physical activity?	☐Yes	☐No
6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?	☐Yes	☐No
8. Do you know of any other reason why you should not do physical activity?	☐Yes	☐No

Medical History Questionnaire

Participant Code:

Section A.

1. When was the last time you had a physical examination?
2. If you are allergic to any medications, foods, or other substances, please name them.
3. If you have been told that you have any chronic or serious illnesses, please list them.
4. Give the following information pertaining to the last 3 times you have been hospitalized. *Note: Women, do not list normal pregnancies.*

	Hospitalization	Hospitalization	Hospitalization
	1	2	3
Reason for hospitalization			
Month and year of hospitalization			

Section B.
During the past 12 months

1. Has a physician prescribed any form of medication for you?	☐Yes	☐No
2. Has your weight fluctuated more than a few pounds?	☐Yes	☐No
3. Did you attempt to bring about this weight change through diet or exercise?	☐Yes	☐No
4. Have you experienced any faintness, light-headedness, or blackouts?	☐Yes	☐No
5. Have you occasionally had trouble sleeping?	☐Yes	☐No
6. Have you experience any blurred vision?	☐Yes	☐No
7. Have you had any severe headaches?	☐Yes	☐No
8. Have you experienced chronic morning cough?	☐Yes	☐No
9. Have you experienced any temporary change in your speech pattern, such as slurring or loss of speech?	☐Yes	☐No
10. Have you felt unusually nervous or anxious for no apparent reason?	☐Yes	☐No
11. Have you experienced unusual heartbeats such as skipped beats or palpitations?	☐Yes	☐No
12. Have you experienced periods in which your heart felt as though it were racing for no apparent reason?	☐Yes	☐No

At present

1. Do you experience shortness or loss of breath while with others your own age?		☐Yes	☐No
2. Do you experience sudden tingling, numbness, or loss of feeling in your arms, hands, legs, feet, or face?		☐Yes	☐No
3. Have you ever noticed that your hands or feet sometimes feel cooler than other parts of your body?		☐Yes	☐No
4. Do you experience swelling of your feet and ankles?		☐Yes	☐No
5. Do you get pains or cramps in your legs?		☐Yes	☐No
6. Do you experience any pain or discomfort in your chest?		☐Yes	☐No
7. Do you experience any pressure or heaviness in your chest?		☐Yes	☐No
8. Have you ever been told that your blood pressure was abnormal?		☐Yes	☐No
9. Have you ever been told that your serum cholesterol or triglyceride level was high?		☐Yes	☐No
10 Do you have diabetes?		☐Yes	☐No
11. How often would you characterize your stress level as being high?		☐Yes	☐No
☐Occasionally	☐Frequently	☐Constantly	
12. Have you ever been told that you have any of the following illnesses or conditions?		☐Yes	☐No
Cardiovascular			
☐Myocardial infraction	☐Arteriosclerosis	☐Heart disease	
☐Coronary thrombosis	☐Rheumatic heart	☐Heart attack	
☐Coronary occlusion	☐Heart failure	☐Heart murmur	
☐Heart block	☐Aneurysm	☐Angina	
☐Hypertension	☐Hypercholesterolemia		
Pulmonary			
☐Asthma	☐Bronchitis	☐Emphysema	

☐Exercise-induce asthma	☐Breathlessness during or after mild exertion		
Musculoskeletal			
☐Osteoporosis	☐Osteoarthritis	☐Low back pain	
☐Prosthesis	☐Muscular atrophy	☐Swollen joints	
☐Orthopedic pain	☐Artificial joints		

Production Record Form

Participant code:

Date:

Experiment Session: ☐Session 1 (Task 1) ☐Session 3 (Task 3)

Please check **every time** you complete one unit of raised deck panel. The one unit of panel is composed of 18 **concrete pavers** in your experiment. The optimal goal is a 10-unit of deck panel completion in one hour.

Example: 70% of completion over your goal

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete	**X**	**X**	**X**	**X**								
						Assi-gned Goal!						

Example: 130% of completion over your goal

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**				
						Assi-gned Goal!						

For your task: You need to fill out this table.

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete												
						Assi-gned Goal!						

Production Record Form

Participant code:

Date:

Experiment Session: ☐Session 2 (Task 2) ☐Session 4 (Task 4)

Please check **every time** you complete one unit of raised deck panel. The one unit of panel is composed of **16 concrete pavers** in your experiment. The optimal goal is a 10-unit of deck panel completion in one hour.

Example: 70% of completion over your goal

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete	**X**	**X**	**X**	**X**								
						Assi-gned Goal!						

Example: 130% of completion over your goal

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**				
						Assi-gned Goal!						

For your task: You need to fill out this table.

Number of one unit of panel	1	2	3	4	5	6	7	8	9	10	11	12
Check **X** in this box when you complete												
						Assi-gned Goal!						

Task Load Index

Title	Endpoints	Decryptions
Physical Demand	Low/High	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand	Low/High	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Mental Demand	Low/High	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
Effort	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
Frustration Level	Low/High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?
Performance	Good/Poor	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

Rating Sheet (Check on each scale at the point that best indicates your experience of the task)

Physical Demand

Low High

Temporal Demand

Low High

Mental Demand

Low High

Effort

Low High

Frustration Level

Low High

Performance

Good Poor

Short Check List Individual Strength Questionnaire (CIS)

Instruction:

On this survey you find 8 statements. With these statements we wish to get an impression of how you have felt during the task. For example:

I feel relaxed:

If you feel that this statement is true, place a cross in the left box; like this:

I feel relaxed	**yes**, that is true	X							**no,** that is not true

If you feel that this statement is not true at all, place a cross in the right box; like this:

I feel relaxed	**yes**, that is true							X	**no,** that is not true

If you feel that this statement is not "yes, that is true", but also not "no, that is not true", place a cross in the box that is most in accordance with how you have felt. For example, if you feel relaxed, but not very relaxed, place a cross in one of the boxes close to "yes, that is true": like this:

I feel relaxed	**yes**, that is true			X					**no,** that is not true

Do not skip any statement and place only one cross for each statement.

1. I feel tired	**yes**, that is true								**no,** that is not true
2. Physically I feel exhausted	**yes**, that is true								**no,** that is not true
3. I feel fit	**yes**, that is true								**no,** that is not true
4. I feel weak	**yes**, that is true								**no,** that is not true
5. I feel rested	**yes**, that is true								**no,** that is not true
6. Physically I feel I am in a bad condition	**yes**, that is true								**no,** that is not true
7. I get tired very quickly	**yes**, that is true								**no,** that is not true
8. Physically I feel in a good shape	**yes**, that is true								**no,** that is not true

Short Stress State Questionnaire

Please indicate how well each word describes how you felt *During The Task*.

Not at all = 1 A little bit =2 Somewhat = 3 Very much = 4 Extremely = 5					
1. Dissatisfied	1	2	3	4	5
2. Alert	1	2	3	4	5
3. Depressed	1	2	3	4	5
4. Sad	1	2	3	4	5
5. Active	1	2	3	4	5
6. Impatient	1	2	3	4	5
7. Annoyed	1	2	3	4	5
8. Angry	1	2	3	4	5
9. Irritated	1	2	3	4	5
10. Grouchy	1	2	3	4	5

Please indicate how true each statement was of your thoughts *While Performing The Task.*

Not at all = 1 A little bit =2 Somewhat = 3 Very much = 4 Extremely = 5					
11. I was committed to attaining my performance goals.	1	2	3	4	5
12. I wanted to succeed on the task.	1	2	3	4	5
13. I was motivated to do the task.	1	2	3	4	5
14. I tried to figure myself out.	1	2	3	4	5
15. I reflected about myself.	1	2	3	4	5
16. I daydreamed about myself.	1	2	3	4	5
17. I felt confident about my abilities.	1	2	3	4	5
18. I felt self-conscious.	1	2	3	4	5
19. I was worried about what other people think of me.	1	2	3	4	5
20. I felt concerned about the impression I was making.	1	2	3	4	5
21. I performed proficiently on this task.	1	2	3	4	5
22. Generally, I felt in control of things.	1	2	3	4	5
23. I thought about how others have done on this task.	1	2	3	4	5
24. I thought about how I would feel if I were told how I performed.	1	2	3	4	5

SF-12v2 Health Survey

The survey form is not physically attached in the Appendix due to a copyright. The license for the use of survey form was obtained via Optum Inc. for this dissertation study from the following link:

http://campaign.optum.com/optum-outcomes/what-we-do/health-surveys/sf-12v2-health-survey.html