

DISSERTATION

A COMPUTATIONAL MODEL AND EMPIRICAL STUDY OF
THE SELF-UNDERMINING PROPOSITION IN JOB DEMANDS-RESOURCES THEORY

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Kevin M. Walters

Department of Psychology

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Colorado State University

Fort Collins, Colorado

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Doctoral Committee:

Advisor: Gwen Fisher

Co-Advisor: Alyssa Gibbons

Benjamin Clegg

Samantha Conroy

Kurt Kraiger

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ABSTRACT

A COMPUTATIONAL MODEL AND EMPIRICAL STUDY OF THE SELF-UNDERMINING PROPOSITION IN JOB DEMANDS-RESOURCES THEORY

The current conceptual model in job demands-resources (JD-R) theory contains eight propositions to explain the dual processes through which job demands and resources influence individuals' strain, motivation, and job performance. Although the theory is generally well-supported and widely-used in industrial-organizational (I-O) and occupational health (OHP) psychology literature, more research is needed to validate its two most recent propositions; that motivation and strain can lead to increases in job resources and demands through job crafting and self-undermining behaviors, respectively. The goal of this study was to test the dynamic variable relationships in the self-undermining proposition through two research methods in an academic context. First, I developed and tested a computational model of the self-undermining proposition based in JD-R theory and other psychological theories and research. Second, I collected longitudinal data from undergraduate students at two U.S. universities and analyzed the data through cross-lagged panel analyses and repeated measures multivariate analyses of variance. The results of the two methods were contradictory. Specifically, the specifications and theoretical assumptions of the computational model resulted in simulations of a perpetual loss spiral via a positive feedback loop, whereas statistical analyses of the longitudinal data did not identify or support the self-undermining proposition. Overall, the results did not support the self-undermining proposition and were influenced by several methodological limitations of this

study, but these limitations and results exemplified several broader limitations of JD-R theory and suggested that the theory is currently inviable and in need of respecification.

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DEDICATION

*In memory of Shirley Anne and Leroy Dale Means,
and their dispositions to generosity, devotion, and teaching.*

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Introduction

Industrial-organizational (I-O) psychology and occupational health psychology (OHP) are two growing fields with considerable implications for society, such as understanding and influencing the health, motivation, productivity, and attitudes of workers and groups. In I-O and OHP research and practice, theories and models are typically used to conceptualize, test, and answer research questions about human behavior, cognition, and well-being in workplace settings (Ganster & Perrewé, 2011; Gliner, Morgan, & Leech, 2017). Although the use of theory is common to all sciences, there has been recent and mounting discussion in organizational disciplines about the need to foster robust science through the appropriate use of theory (Grand et al., 2018). Specifically, organizational sciences should be “theory-oriented,” rather than theory-driven or theory-dependent, by robust theories that are evidence-based, comprehensively explain natural phenomena, and are treated “as a means to an end, not an end in and of itself” (Grand et al., 2018, p. 12). Moreover, the overwhelming majority of current theories in organizational sciences are informal (i.e., verbal) and therefore limited by “the ambiguity of natural language and the capacity of the human mind” (Vancouver & Weinhardt, 2012, p. 604), as opposed to theories developed with formal tools such as mathematical models, simulations, and logic (Adner, Pólos, Ryall, & Sorenson, 2009). It is therefore of utmost importance that current and future psychology theories are subjected to rigorous testing, replication, refinement, and formalization.

Job demands-resources (JD-R) theory is one oft-referenced example of a theory used in I-O and OHP research (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). In a recent review of JD-R theory, Bakker and Demerouti (2017) summarized the 15 years of theory development and empirical testing that led to the current conceptual model (see Figure 1). There are two

primary processes in the model that ultimately influence an individual's job performance, referred to as the health impairment process and the motivational process. Bakker and Demerouti described eight propositions of JD-R theory that together constitute the overall model and its dual processes. Although most of these propositions are empirically supported, the extent of evidence for the integrated and isolated processes varies. For example, the eighth proposition posits that individuals may experience "loss spirals" at work in which high job demands relate to elevated strain and health impairment, which further lead to workers perceiving and creating more job demands over time through self-undermining behaviors (Bakker & Demerouti, 2017). Although some research has directly tested this proposition (e.g., Bakker & Wang, 2016), and other literature has indirectly supported the self-undermining proposition (e.g., Demerouti, Bakker, & Bulters, 2004), it needs further testing and support (Bakker & Demerouti, 2017). The aim of this study was to therefore contribute to research literature by assessing the eighth proposition of JD-R theory via two research methods. I next describe these two methods.

First, to test the self-undermining proposition in consideration of the limitations of current organizational science theory, computational modeling is an especially applicable research methodology. Computational modeling is a recent and growing approach in I-O psychology (Cortina, Aguinis, & DeShon, 2017; Grand et al., 2018; Kozlowski, Chen, & Salas, 2017; Salas, Kozlowski, & Chen, 2017) that enables researchers to explicitly and mathematically specify the parameters of theoretical models in dynamic computer simulations (Vancouver & Weinhardt, 2012). The output of such simulations may aid or benefit researchers in multiple ways, such as in gaining more understanding of the complex relationships and underlying processes of variables in the model, as well as in acquiring data and output that may be compared to empirical evidence acquired from human subjects. In this research context, the conceptual

JD-R model may be computationally specified and tested to provide further evidence for the purportedly involved processes. In other words, simulating the JD-R model in an isolated environment – one that is computationally and mathematically specified in explicit terms by the researcher – may enable a formal examination of the logical premises of the self-undermining proposition and/or the overall JD-R theory.

Second, in addition to articulately evaluating the underlying processes of the self-undermining proposition, the latter benefit of computational modeling is also relevant here. Specifically, contemporaneous empirical study of the self-undermining proposition can provide additional support in two ways. First, given that the self-undermining proposition needs further empirical support, the study tests and results may be used to iterate and provide evidence for its validity. Second, the study results may be compared to the computational model output to provide additional investigation and understanding of the conceptual model. I next further describe JD-R theory, computational modeling, longitudinal research design, and the corresponding hypotheses of this study.

Theory, Design, and Hypotheses

Job demands-resources theory. JD-R theory was first proposed by Demerouti et al. (2001) as a model to explain burnout, a phenomenon common to all jobs in which workers are chronically exhausted, cynical, and less effective (Maslach, Schaufeli, & Leiter, 2001). A core tenet of JD-R theory is that all job aspects can be operationalized as either *demands* that require sustained effort at a psychological or physiological cost to workers, or as *resources* that enable workers to fulfill their tasks by promoting workers' development and/or by reducing demands and their costs (Proposition 1; Bakker & Demerouti, 2017). Resources may be further conceptualized as *job resources* (e.g., support, autonomy, etc.) or *personal resources* (e.g., self-

efficacy, optimism, etc.), although they both play similar roles in the model (Proposition 5). Specifically, the JD-R is a dual process model and posits that job and/or personal resources instigate motivational processes, whereas demands instigate health impairment processes (Proposition 2). Furthermore, job resources may especially influence motivation when job demands are high (Proposition 4). Bakker and Demerouti also stated that motivated workers exhibit better job performance (Proposition 6) and are likely to engage in job crafting behaviors (such as seeking out additional resources and challenges or reducing demands; Demerouti, 2016; Petrou, Demerouti, Peeters, Schaufeli, & Hetland, 2012) that promote “gain spirals” as workers subsequently acquire more resources and motivation (Proposition 7). Additionally, resources may also act as a “buffer” (i.e., an interaction) against the effect of job demands on strain outcomes (Proposition 3). For example, a customer service representative may experience mental and physical exhaustion (high strain) if consistently exposed to unpleasant and irate clients (high job demands), but they may be notably less exhausted if they have supportive coworkers or the autonomy to take breaks (high resources). Nonetheless, strain is a consequence of job demands in many contexts, and strained employees may indirectly increase their job demands in “loss spirals” by engaging in self-undermining behaviors such as making mistakes and creating conflicts at work (Proposition 8).

Although the first six propositions have received intensive scrutiny (Bakker & Demerouti, 2017; 2018; Bakker, Demerouti, & Sanz-Vergel, 2014), the proposed loss and gain spirals have substantially less empirical support (Bakker & Demerouti, 2017). The first indirect evidence for loss spirals came when longitudinal researchers found that demands predicted later employee strain (a causal effect) and strain also predicted higher future job demands (a reversed causal effect; e.g., Bakker, Schaufeli, Sixma, Bosveld, & Van Dierendonck, 2000; Demerouti et

al., 2004; Demerouti, Le Blanc, Bakker, Schaufeli, & Hox, 2009; Zapf, Dormann, & Frese, 1996). Similar causal and reversed causal effects of resources and motivation provided initial support for gain spirals (e.g., Hakanen, Perhoniemi, & Toppinen-Tanner, 2008; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009). Thus, literature does support the premise of loss and gain spirals, but there is still an imminent need for both general research on the spirals (Bakker & Demerouti, 2017) and research to systematically assess the dynamic relationships among JD-R variables (Schaufeli & Taris, 2014). Accordingly, this study contributes to psychology literature by testing the self-undermining proposition of JD-R theory.

The term “self-undermining behaviors” was first proposed by Bakker and Costa (2014, p. 115) to describe “behavior that creates obstacles that may undermine performance.” Or, more informally and colloquially, these behaviors could be considered “shooting oneself in the foot” (Bakker, 2016). Using the previous example, if a customer service representative is incessantly exposed to irritable customers without the autonomy, support, or other resources to buffer negative outcomes, then the individual is likely to experience exhaustion and/or other forms of strain. In such an exhausted state, the individual might fail to regulate their tone and emotional expressions (a form of emotional labor; Grandey, 2000), thereby amplifying the conflict with a client and leading to more job demands such as emotionally demanding conversations with coworkers or supervisors. Though hypothetical, this example encapsulates the premise of self-undermining behaviors augmenting individuals’ job demands and thereby perpetuating and/or strengthening the loss spiral.

Although past longitudinal research has supported the validity of loss spirals in the JD-R conceptual model, almost no research has directly tested the self-undermining proposition. For example, Bakker and Wang (2016) developed a measure of self-undermining behaviors and

conducted preliminary research to support the construct's validity. Specifically, Bakker and Wang collected data from seven samples across five countries and analyzed structural models to determine that self-undermining behaviors positively related to work pressure, emotional demands, exhaustion, and burnout (Bakker, 2016). Nonetheless, the research is not yet published as of this study and others have noted methodological limitations in past studies of loss spirals (Schaufeli & Taris, 2014).

Furthermore, although the recent additions of loss and gain spirals further expand JD-R theory to incorporate dynamic temporal relationships among job characteristics, well-being, and behavior, current research on these integrated concepts generally fails to provide or explain JD-R processes' underlying mechanisms (Schaufeli & Taris, 2014). For example, the current JD-R model does not consider cognition in the self-undermining behavior process. When designing this study, a relevant question arose about the impact of individuals' awareness on self-undermining behaviors. That is, does one's awareness of self-undermining tendencies alter their behaviors? And, assuming the self-undermining proposition is valid, how (or under what circumstances) might awareness therefore impact the relationships in the model? To elucidate this question, consider two individuals in the throes of loss spirals; self-undermining behaviors are increasing demands and strain, thereby reinforcing further similar behaviors. One individual is consciously aware of their behaviors, whereas the other is not. Would this awareness alter the strength, speed, and/or duration of the spiral between individuals in some manner?

The question of cognition's role in the self-undermining proposition reinforces Bakker and Demerouti's (2017) assertion that future research should investigate the underlying psychological and physiological processes involved with human response to environmental characteristics. The aim of this study was therefore to answer this call through computational

modeling, a method that enables logical specification and testing of dynamic theoretical propositions (i.e., the self-undermining process) while also considering other factors or variables (e.g., cognition or behavioral awareness) that may influence processes in the model. A concurrent study aim was to use longitudinal research to further assess and interpret the self-undermining proposition's dynamic and causal relationships over time. I next describe these two methods and present the study hypotheses.

Computational modeling. Vancouver and Weinhardt (2012, p. 603) succinctly and analogously described that “computational modeling is to theories as statistical analysis is to data; that is, it is a tool useful to support inferences when the predicates (i.e., theory/data) are particularly complex.” Thus, in this study computational modeling served as a tool to specify, test, and better understand the purported relationships of JD-R theory for comparisons to empirical results. Computational modeling has long been utilized in other fields, such as the physical and biological sciences, to simulate and assess the dynamic processes of theories and systems involving many variables (Weinhardt & Vancouver, 2012). Importantly, computational modeling is not intended to serve as an indistinct proxy for the informal (i.e., verbal) theory or conceptual model; rather, it is an algorithmic simulation of the processes conveyed by the theorist, as specified in the collection of parameters used in the simulation (Vancouver & Weinhardt, 2012).

There are various approaches and perspectives to computational modeling in psychological science, such as agent-based modeling (Bonabeau, 2002; Siegfried, 2014; Smith & Conrey, 2007), system dynamics modeling (Homor & Hirsch, 2006; Sastry, 1997; Sterman, 2001), ACT-R (Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin, 2004; Anderson, Matessa, & Lebiere, 1997; Taatgen, Lebiere, & Anderson, 2006), and other computational and/or neural

networking architectures. Although computational modeling has been used in various psychological disciplines, such as cognitive scientists' use of ACT-R to model human thought processes and their relation to brain architecture and activity (i.e., "an integrated theory of the mind"; Anderson et al., 2004), the technique has yet to emerge as common practice in I-O psychology research. Nonetheless, a small proportion of researchers have used computational modeling to assess organizational issues, such as Hanisch, Hulin, and Seitz's (1996) WORKER software that modeled employee withdrawal and significantly impacted the understanding and direction of withdrawal research (Hulin, Miner, & Seitz, 2002; Ilgen & Hulin, 2000b). In addition to many other empirical examples of computational modeling in organizational sciences (e.g., McPherson, 2000; Vancouver, Putka, & Scherbaum, 2005; Vancouver, Tamanini, & Yoder, 2010), some authors have published chapters (e.g., Hulin et al., 2002; Zickar, 2006) and books (e.g., Ilgen & Hulin, 2000a; Taber & Timpone, 1996) to integrate the method into our research. More recently, Weinhardt and Vancouver (2012) argued for an adoptive approach of computational modeling in organizational sciences. Thus, although computational modeling is potentially an intimidating, novel, or otherwise unfamiliar technique for many I-O researchers, there are many examples and introductory texts to reference in such endeavors.

One example especially relevant to this study is from Vancouver and Weinhardt's (2012) overview of computational modeling for micro-level organizational researchers. In the overview, Vancouver and Weinhardt proposed that informal theoretical models of job attitudes and stress may benefit from formal computational modeling, especially those that incorporate path diagrams and feedback loops. Furthermore, Vancouver and Weinhardt used Edwards' (1992) cybernetic model of stress, coping, and well-being to provide a step-by-step example to developing and testing a formal computational model. In this and several other articles by these

authors (e.g., Vancouver et al., 2005; Vancouver, Weinhardt, & Schmidt, 2010; Vancouver, Weinhardt, & Vigo, 2014), Vancouver and Weinhardt used perceptual control theory as the theoretical foundation to build computational models.

Perceptual control theory was first described by Powers (1973) and broadly states that the purpose of humans' (and other living organisms') behaviors is to regulate or control perceptions of external stimuli. Essentially, external or environmental stimuli prompt the *input* to the system (i.e., human perception of the *external or environmental variable*) in reference to a *comparator* (typically goals or desires), and consequential *discrepancies or errors* between the input and comparator (inconsistency between perceptions and desires) thereby prompt the *output* (behaviors) that may influence the environmental variable and our subsequent perceptions, further perpetuating the cycle via feedback loops. Figure 2 provides a visual depiction of a basic computational model based in perceptual control theory. Following the examples of Vancouver and Weinhardt (2012) and Powers, in this study I applied perceptual control theory to develop a computational model of JD-R theory that accounted for the dynamic and cyclical effects of demands, strain, self-undermining behaviors, and performance in the self-undermining proposition.

The conceptual model in JD-R theory is more complex than Edwards' (1992) cybernetic model, but the JD-R is nonetheless a prototypical example of an informal model utilizing path diagrams and feedback loops. For example, Propositions 7 and 8 are both feedback loops, in that motivation and strain may alter individuals' job resources and demands via job crafting and self-undermining behaviors, respectively. These fluctuations in demands and resources will therefore further affect individuals' strain and motivation, leading to continued loss and gain spirals and consequential dynamic effects on performance. Perceptual control theory may therefore serve as

an appropriate foundation for a comprehensive computational model of JD-R theory.

Nonetheless, computational models are often developed incrementally with sophisticated models built upon earlier, more elementary models (Vancouver & Weinhardt, 2012; Whicker & Sigelman, 1991). Furthermore, simple models can and have been influential in both research and practical contexts (e.g., Dawes, 1979; Dawes & Corrigan, 1974). Therefore, the goal of the first research method was to build, test, and evaluate an elementary computational model that could be modified and/or expanded in future research on JD-R theory.

Longitudinal design and study hypotheses. Along with computational modeling, this study utilized a longitudinal research design to answer Bakker and Demerouti's (2017) call for studies assessing JD-R theory propositions over time. This approach mirrored that of other JD-R researchers, such as Demerouti et al.'s (2009) study of the reciprocal relationships between job demands, presenteeism, and burnout (see also: Demerouti et al., 2004; Hakanen, Schaufeli, & Ahola, 2008). Specifically, at three time points (lagged at two-week intervals) I measured demands, strain, self-undermining behaviors, and performance in a sample of undergraduate students to assess loss spirals over time

Undergraduate samples have been criticized regarding the generalizability and external validity to the entire population of working adults, given the likelihood of part-time employment, the additional demands of attending secondary education, and the typical lack of professional or career experience (see Landers & Behrend, 2015). Although researchers have provided counterarguments and evidence to the contrary (e.g., Vanhove & Harms, 2015), effective sampling is nonetheless especially relevant and important in I-O psychology research (Fisher & Sandell, 2015). For example, authors have identified that inadequate sampling can bias study results (e.g., Grzywacz, Carlson, & Reboussin, 2013) and that the research itself can even be

biased if effective sampling strategies are used in unrepresentative populations or contexts (Michel, Hartman, O'Neill, Lorys, & Chen, 2015). In other words, researchers should consider both the research question(s) and the population of interest when designing studies.

In this study, the goal was to therefore extend JD-R theory to specifically assess academic demands, health outcomes, behaviors, and performance of college students. Given the absence of theories on student well-being and performance, researchers have argued that job stress theories can and should be utilized to understand and influence student well-being and performance (Cotton, Dollard, & de Jonge, 2002). Moreover, the demands and pressures of academic programs are comparable to those of individuals at work (Noh, Shin, & Lee, 2013; Parker & Salmela-Aro, 2011), and researchers have applied OHP theories and models to academic contexts (Pluut, Curşeu, & Ilies, 2015). For example, JD-R theory has been used as a framework to study topics such as work-school conflict and student health outcomes (Park & Sprung, 2013) and student stress and academic performance (Pluut et al., 2015). More broadly, psychology researchers have generally recognized that school stress can conflict with students' other work and family roles (Olson, 2014; Park & Sprung, 2013) and also impact students' health behavior (Butler, Dodge, Kama, & Faurote, 2010; Dalton & Hammen, 2018), emotional well-being (Zhang & Zheng, 2017), and academic performance (Cheng & Catling, 2015; Frazier, Gabriel, Merians, & Lust, 2018; Bresó, Schaufeli, & Salanova, 2011). Moreover, authors in recent I-O psychology literature have pointedly argued to expand the field's scope to include underrepresented and/or vulnerable populations with an emphasis on the consideration of all aspects of human well-being (Gloss, Carr, Reichman, Abdul-Nasiru, & Oestereich, 2017). Well-being is a primary concern of OHP research and practice (Tetrick & Quick, 2011), as the field developed at the intersection of multiple disciplines that jointly emphasize the importance

of individual and environmental factors related to health (Sauter & Hurrell Jr., 2017). Thus, I assert that the extension of JD-R theory to college students' experiences was warranted on both methodological (i.e., aligning the sample and the research question) and humanist (i.e., considering all aspects of well-being) bases. To test the self-undermining process in a longitudinal study of college students, I proposed the following four hypotheses that reflect the underlying assumptions of the self-undermining proposition:

H1: Demands predict strain outcomes. Specifically, increases in academic demands predict increases in strain outcomes.

H2: Strain outcomes predict self-undermining behaviors. Specifically, increases in strain outcomes predict increases in self-undermining academic behaviors.

H3: Self-undermining behaviors predict demands. Specifically, increases in self-undermining behaviors predict increases in academic demands.

H4: Strain outcomes predict performance. Specifically, increases in strain outcomes predict decreases in academic performance.

Overall study design and temporal parameters. This study involved two designs – computational modeling and longitudinal research – that together enabled an in-depth assessment of the self-undermining proposition in JD-R theory. To optimize comparisons of the study results, each design incorporated weekly units of time for all study variables (i.e., demands, strain, self-undermining behaviors, and performance). Specifically, I specified the computational model settings to include the unit of time as “week” and simulate five time steps. This paralleled the longitudinal study methods, as data were collected at two-week intervals and all survey items prompted participants to respond to the items as they pertained to their experiences over the prior two weeks (i.e., the time between surveys).

I next describe the two research designs in detail, including further description of the parameters (temporal and otherwise) of each method. First, I describe the procedure of building and evaluating a computational model of the self-undermining proposition. Second, I describe the longitudinal methods, analyses, and results that empirically tested the self-undermining proposition's dynamic processes. Third, I interpret and compare the integrative results of simulations and statistical analyses. Finally, I conclude with discussions of the methodological and theoretical limitations and implications of this study.

Methods – Computational Modeling

I developed the computational model using Vancouver and Weinhardt's (2012) four recommended steps: 1) identify a problem; 2) define the system; 3) build the model; and, 4) evaluate the model.

Step One: Problem Identification

First, the identified problem was the need to further test Proposition 8 of JD-R theory, which postulates that self-undermining behaviors operate as a "loss spiral" and increase demands for strained individuals. Specifically, the self-undermining proposition suggests that demands lead to strain outcomes that consequentially negatively influence individuals' performance and positively influence self-undermining behaviors. Furthermore, self-undermining leads to subsequent increases in job demands, and these relationships are expected to augment and strengthen over time (Bakker & Demerouti, 2017).

System dynamics computational modeling was appropriate in this context, given that JD-R theory is currently conceptualized as an informal model of dynamic individual-level processes that explain psychological and behavioral phenomena. Computational modeling is useful in theory refinement (Edwards, 2010), and existing informal theory can provide a useful

starting point to develop formal models (Vancouver & Weinhardt, 2012). Moreover, system dynamics is suitable for macro- and micro-level computational modeling and incorporates a cybernetic architecture that accounts for dynamic homeostasis (Vancouver, 1996; Vancouver & Weinhardt, 2012). Homeostasis is a core tenet of early stress theories (e.g., Selye, 1955; 1976) that were influential in JD-R theory development (Bakker & Demerouti, 2017), and current stress researchers recognize the dynamic nature of homeostasis (e.g., Ganster & Perrewé, 2011; Ganster & Rosen, 2013).

Step Two: System Definition

System definition involves “identifying the unit(s) of analysis, the boundary of the problem to be simulated, the restrictions (e.g., time bounds), and variables” (Vancouver & Weinhardt, 2012, p. 607). I defined the computational model system in consideration of the overall goal to include variables, boundaries, and restrictions that could both simulate intra-individual processes of the self-undermining proposition and also most directly compare to longitudinal results. I next describe the system definition in reverse order (i.e., variables, boundaries and restrictions, and the unit/level of analysis) for clarity.

First, in conceptual and system dynamics modeling terms, the initial model variables (see Figure 3) included demands (the *environmental variable*), which were *disturbances* that initiated the simulation. Individuals’ perceptions (the *input*) of demands were compared to individuals’ desires (the *desire* or *goal*) of demands in the *comparator* function. If imbalances (*discrepancies*) between perceptions and desires were present, then strain (the result of the *comparator*) influenced individuals’ behavior (the *output*), such that those perceiving more demands than desired would engage in self-undermining behaviors that further augmented demands. Strain also influenced individuals’ performance, another outcome added to the model. In more technical

modeling terms, the variables involved include individuals' *perceptions* (1) that were a function of/refer to *demands* (2), which were a function of *self-undermining behaviors* (3), which, along with *performance*, were a function of the *strain* (4) resulting from the discrepancy between individuals' *desires* (5) and perceptions of demands. See Table 1 for a full description of the variables.

Second, the boundary and restrictions of the current model were specified to (a) fulfill the goal of building a simple model (Repenning, 2003; Vancouver & Weinhardt, 2012; Whicker & Sigelman, 1991), and (b) parallel the boundary and restrictions of the longitudinal study to enable comparisons between computational and statistical results. Specifically, the model was limited to the self-undermining proposition of JD-R theory, rather than the entire JD-R conceptual model, and the restrictions (i.e., time bounds) of the model matched those of empirical data collection (five weeks). Although more research is needed to assess microprocesses within the JD-R model and the effects of fluctuations (i.e., of demands, resources, and other JD-R variables) at shorter time intervals (e.g., hourly, daily, etc.; Bakker & Demerouti, 2017), these issues were not the focus or scope of this study.

Third, given that JD-R theory is a psychological theory, the unit of analysis was the individual. Modelers should also prudently consider the level(s) of analysis, as processes at one level may influence or account for processes at another level (Weinhardt & Vancouver, 2012). Moreover, researchers should choose their level of analysis based on the phenomenon of interest (Sun, Coward, & Zenzen, 2005; Weinhardt & Vancouver, 2012). In this study, I chose an “agent” level model, or the “psychological level, which covers individual behaviors, beliefs, concepts, and skills” (Sun et al., 2005, p. 9), to simulate self-undermining processes via the individual-level variables (i.e., perceptions, strain, behaviors, etc.) and their respective

relationships. In other words, the system in the overall model structure (see Figure 3) represented the agent, or the individual and their intra-individual psychological processes.

Although researchers have called for investigations of JD-R model processes at micro- and macro-levels (e.g., from episodic individual experiences to group-level phenomena; Bakker & Demerouti, 2017), I chose an agent level model given that this was an initial attempt to formally model JD-R theory principles. Nonetheless, JD-R researchers may consider alternative models in their research. For example, a more elaborate cross-level (also called meso-level) approach could entail intra-agent level (i.e., within-agent, or lower-level) processes that influence agent level processes (Weinhardt & Vancouver, 2012). Intra-agent models of the self-undermining proposition could include components or modules (see Sun et al., 2005; Weinhardt & Vancouver, 2012) with individual feedback loops and functions to more elaborately specify the process of perceiving demands, experiencing strain outcomes, and behaving accordingly. In other words, rather than including only one cybernetic structure (as in Figures 3-4), multiple intra-agent cybernetic structures could be included in place of the model variables (i.e., a feedback loop each for perceptions, strain, demands, etc.); these intra-agent processes would therefore influence or determine the overall agent level processes. Furthermore, one could rather (or simultaneously) include inter-agent (i.e., between-agent or higher-level) processes in the model to simulate the ways that agent level psychological processes influence group behavior.

Step Three: Model Building

Overview of the building process. I completed step three by following the recommendations of Vancouver and Weinhardt (2012, p. 608) to use Vensim®, a “set of user-friendly, highly sophisticated software packages devoted to computational model building.”¹ The

¹ In this study I used Vensim® Personal Learning Edition (PLE), a free version for academic or educational use. More information on this and other versions is available at <https://vensim.com>.

model building process involved specifying model settings (i.e., setting the boundaries and restrictions), visually building the model, and specifying the functions of model variables. However, the process of developing, evaluating, and interpreting a computational model is dynamic and parallel rather than sequential in nature, much like psychometric research methods. For example, rather than involving serially influential analytical steps, scale development often involves interpretations (e.g., of item factor loadings) influencing subsequent decisions (e.g., dropping items) that also involve reconsidering previous decisions, interpretations, and/or information (e.g., revisiting item wording and scale content validity).

Just as there is no single “correct” procedure for any given scale development project, computational modeling is a dynamic process that involves objective and subjective components at multiple decision points (hence the prevalence of researchers in other fields simultaneously building and comparing multiple alternative computational models; see Pitt, Myung, & Zhang, 2002). Moreover, computational modeling often necessitates a non-linear analytical process of integrating new information (e.g., simulated results after model respecification) with past information (past simulations or model specifications) to inform present decisions (to modify or retain the model). In other words, researchers may need to “backtrack” after partially or fully specifying a model and realizing it is inviable, perhaps due to insufficient, atheoretical and/or implausible explanations or simulations of the dynamic system of interest (Vancouver & Weinhardt, 2012). Such occurrences may indicate limitations of the informal theory in question, in that it provides the basic causal structure or architecture for the computational model but lacks enough detail to fully specify the model (Busemeyer & Wang, 2000). Or, inviable models could indicate misspecifications or errors by the modeler that result in erroneous downstream effects. Vancouver and Weinhardt’s (2012) computational model development of Edwards’ (1992)

cybernetic stress theory provided several examples of respecifications in cases of both theoretical limitations and prior misspecifications.

When respecification decisions are necessary, they may be informed by logic, deduction, and assessments of the simulated model output. Vensim® also provides graphs with the variables as individual lines that fluctuate in their values (the y-axis) across time (the x-axis). One additional method to assess complete (i.e., working but perhaps incorrectly specified) models is *sensitivity analysis* (Davis, Eisenhardt, & Bingham, 2007), “a primary method for evaluating models” (Vancouver & Weinhardt, 2012, p. 614) in which researchers alter the initial and/or constant values of variable parameters in the simulated model and evaluate the consequential changes to model variables’ trajectories over time. This process provides an opportunity to assess how the variables simultaneously interact and influence one another at different starting values.

Altering mathematical functions and/or adding variables to remedy inviable models may necessitate “ad hoc assumptions” about the underlying structure and processes of the model (Busemeyer & Diederich, 2010; Vancouver & Weinhardt, 2012). Such assumptions are typically subjective, have different empirical implications, and may go beyond principles of the informal theory. Therefore, researchers should base ad hoc assumptions in sound scientific principles (i.e., empirical evidence or other theory) to avoid inapt, erroneous, or atheoretical model specification and, conversely, to enable model identification and inform new a priori predictions in current and future research.

Prior to model building in this study, I aimed to limit ad hoc assumptions but also recognized that insufficiencies could be unavoidable given the absence of research explaining the underlying psychological mechanisms of the informal JD-R theory (Bakker & Demerouti, 2017; Schaufeli & Taris, 2014). In other words, although I aimed to inform model building decisions

with JD-R theory, I anticipated that the current informal theory may nevertheless provide insufficient evidence to formally depict and/or explain the self-undermining proposition given the limitations of informal verbal theories (see Adner et al., 2009; Farrell & Lewandowsky, 2010; Johnson-Laird & Young, 2008; Vancouver & Weinhardt, 2012). If such instances arose, I aimed to remedy the issues and inform ad hoc assumptions by reflecting on JD-R theoretical principles, reviewing relevant I-O and OHP literature, troubleshooting and altering model specifications, conducting sensitivity analysis, and/or by adding variables to the model. I next describe the model building process of selecting model settings, visually constructing the model, and specifying the model values and functions.

Model settings. Vensim® enables modelers to specify time in units that are meaningful to the study, ranging from seconds to years. I therefore specified the model time bounds as five weeks (i.e., “Initial Time” = 0, “Final Time” = 5, “Units for Time” = Week) using the default equation integration settings (i.e., “Integration Type” = Euler), following other researchers’ examples when details regarding the timing of processes are generally unknown (e.g., Vancouver, Tamanini et al., 2010) and given that Euler integration is appropriate in “business and social models where the distinction between difference and differential equations is blurry” (Ventana Systems, Inc., 2012). In non-technical terms, at each week (i.e., unit of time) in the model, this setting specified the Vensim® software to update variables’ values using the prior weeks’ values and the functions specified for each variable.

Visual model construction. I next visually constructed the model in Vensim® to contain the variables and corresponding arrows. See Figure 2 for a basic example of a computational model, Figure 3 for the initial visual model (i.e., the proposed model prior to specifying any functions) and Figure 4 for the final visual model in this study. Computational modeling

diagrams are distinct from other graphical diagrams or models in psychology research (e.g., structural equation modeling) in that the arrows do not always represent causality. Rather, the arrows depict the variables, constants, and/or coefficients involved in each *function* (i.e., the mathematical relationship between values of inputs and outputs; Ross, 2011). Variables not receiving arrows or surrounded by boxes (i.e., *exogenous* or external variables) are typically constants or parameters that operate as inputs to the functions in the model. The variables receiving arrows (i.e., *endogenous* or internal variables) are functions of inputs and outputs and therefore change over time. For clarity, I surrounded endogenous variables with boxes (see Vancouver & Weinhardt, 2012) and labeled endogenous variables to represent the result of each function. An example is the Strain label in Figure 3 that represents the output of the function as calculated by an equation of the mathematical relationship between perceptions and desires of demands.² Furthermore, I capitalized the labels of dynamic variables. Dynamic variables “have memory in that they change their level depending on inflows and outflows” (Vancouver & Weinhardt, 2012 p. 611), and are sometimes referred to as stocks “because they behave like stocks in an inventory” (Weinhardt & Vancouver, 2012). In other words, a dynamic variable represents a construct in which the direction and rate of change are determined by both the prior value of that construct and the current values of other constructs. For example, in the initial model (Figure 3) Strain at week two is a function of both Strain at week one and perceptions and desires at week two. On the contrary, changes in non-dynamic endogenous variables are determined only by values at that timepoint. For example, in the initial Figure 3 model

² Strain in this study represented the comparator function in control theory, and researchers have labeled the comparator as either the function itself (e.g., Hulin & Judge, 2003) or the result (e.g., Edwards, 1992). I chose the result for consistency and to be clear in other equations that include the label (Vancouver & Weinhardt, 2012).

perceptions at week two is a function of only Demands at week two. I further describe the conceptual and mathematical properties of all model variables in the following section.

Model specification. System dynamics modeling involves applying math to stipulate the equations (i.e., the functions) or values (i.e., the constants and/or bounds) that will transform data in the model, and this process therefore requires some amount of prior knowledge about the nature of the variables and their relationships (Vancouver & Weinhardt, 2012). That is, the chosen specifications of exogenous and endogenous variables should be both theoretically and mathematically meaningful. For example, computational model functions in cognitive sciences are often specified to mirror the linear, exponential, logarithmic, or differential relationships between variables that has been determined in research. Although this may yield simulations that are most reflective of current literature and knowledge, the cognitive sciences are comparatively far more sophisticated than organizational sciences in the use of computational models and supportive literature to specify precise relationships among constructs (see Dayan & Abbott, 2001; Ivancevic & Ivancevic, 2007; Lewandowsky & Farrell, 2011; Sun, 2006). I therefore sought to apply basic theoretical and mathematical principles to this computational model given that research supports the utility of this approach (Dawes, 1979; Dawes & Corrigan, 1974; Vancouver & Weinhardt, 2012; Whicker & Sigelman, 1991) and given the paucity of evidence for precise variable relationships in the self-undermining proposition (Bakker & Demerouti, 2017). See Table 2 for a full description of the types, mathematical equations, and Vensim® functions of all variables included in the final model.

Initial exogenous variables. I first specified the model's initial exogenous variables (i.e., constants or parameters) as values or numbers that mathematically accounted for the theoretical properties of the variable in the model. For example, a value of 0 may represent a natural origin

or homeostatic level (Vancouver & Weinhardt, 2012), such as in additive relationships in which the initial simulation would assume no effect of the exogenous variable in question (i.e., +0 or -0 yields no change). Or, a value of 1 may represent a coefficient or weight (Vancouver & Weinhardt, 2012), such as in multiplicative effects (e.g., moderation or interaction) that are absent in the initial model (i.e., $\times 1$ yields no change). In simulations, Vensim® provides sliding scales for exogenous variables – with specifiable intervals and outer bounds – to aid in sensitivity analyses and interpretations.

In the initial model, I specified desires to represent the natural origin (0), or individuals' initial desired amount of academic demands. In later sensitivity analyses, positive values of desires would therefore represent increases in desired demands, and negative values would represent decreased desires. Additionally, I specified *initial demands* at 1 to begin with a model in which demands (1) were greater than individuals' desires (0) to prompt the loss spiral.

Endogenous variables. I then specified endogenous (i.e., time-varying) variables in the model. Unlike exogenous variables, endogenous variables are functions of other variables and thus are specified as equations rather than specific values. Although all endogenous variables have boxes in the visual model, only dynamic variables are capitalized. I next describe the process of applying math to each function, including further discussion of dynamic variables and ad hoc assumptions that were necessary to fully specify the model.

Perceptions. In the initial model, perceptions only received an arrow from Demands. A simple function could represent this relationship without altering the model, such as:

$$\text{perceptions} = \text{Demands} \quad (1)$$

This would imply that individuals' perceptions of demands are exact and unbiased. For example, consider environmental demands with an arbitrary value of 1 on a hypothetically perfect

objective measure. The equation above states that individuals' internal perceptions of demands would *also* equal 1 on an equivalently perfect subjective measure, regardless of context or individual differences. This was generally implausible and exemplified Vancouver's (2012) recommendation in a similar context (i.e., when an endogenous variable initially received only one arrow from another endogenous variable) that "in general, it is good form to include a variable that might qualify the effect of another variable" ("Adding Math to describe relationships," para. 4).

Adding a variable to qualify the effect of Demands on perceptions necessitated an initial ad hoc assumption based in theory. Specifically, the transactional theory of stress (Lazarus, 1966; Lazarus & Folkman, 1984; 1987) posits that strain outcomes are a product of individuals and their environments. A premise of this theory is the importance of *cognitive appraisals* that may explain individual differences in perceptions of demands. In simple terms, demands perceived as stressful to one individual might be perceived differently by other individuals. To elucidate this phenomenon, researchers have conceptualized demands as either "hindrances" (that elicit negative outcomes) or "challenges" (that require energy but may elicit gains like engagement or opportunities for growth; Bakker & Demerouti, 2017; Crawford, LePine, & Rich, 2010; Van den Broeck, De Cuyper, De Witte, & Vansteenkiste, 2010). Moreover, JD-R research has identified the importance of cognitive appraisal in the relationship between demands and outcomes (e.g., Gomes, Faria, & Gonçalves, 2013; Hu, Schaufeli, & Taris, 2013), supporting the premise that it could qualify the perceptions function in this model given that Strain received the output of the perceptions function. Therefore, I modified Equation 1 to be the following:

$$\text{perceptions} = \text{Demands} + \text{appraisal} \quad (2)$$

Equation 2 reflected an underlying assumption that cognitive appraisal may be conceptualized as a parameter in which positive values represent a bias to perceive hindering demands, whereas negative values represent biases to perceive challenging demands. Accordingly, appraisal values increase or decrease output values of the perceptions function. The additive component here suggests that the bias is linear, meaning that the effect of cognitive appraisal is unvarying across all levels of Demands. Literature on this effect is unclear, in that the demands-strain relationship is purportedly impacted by a cognitive appraisal process that also involves individuals' coping behaviors (Folkman, Lazarus, Dunkel-Schetter, DeLongis, & Gruen, 1986; Lazarus & Folkman, 1984). Moreover, the cognitive appraisal process may variably impact the demands-strain relationship via an interaction between cognitive appraisal (i.e., of the demands and what is at stake) and coping (i.e., problem-focused or emotion-focused; Folkman et al., 1986; Forsythe & Compas, 1987). To fully specify the varying effects of appraisal and coping extended beyond the goal of this study. I therefore retained the additive effect in Equation 2 and specified 0 (the natural origin) as the value of appraisal.

Strain. I next specified the Strain function (i.e., the comparator function in control theory) as a dynamic variable, as the premise of loss spirals in the self-undermining proposition relies on a core assumption of progressively worsening strain. In other words, values of strain at later time points are at least partially contingent on strain values at prior time points. Theory and research generally support this notion. For example, the allostatic load model suggests that chronic exposure to stressors may alter various response systems (e.g., cardiovascular, neuroendocrine, etc.) to pathological levels and yield detrimental psychological and physiological outcomes (Ganster & Perrewé, 2011; Ganster & Rosen, 2013).

Strain therefore represented a dynamic variable that is a function of the discrepancies between perceived and desired demands. In system dynamics modeling, dynamic variables are mathematically represented as integral functions to model time continuously (Vancouver & Weinhardt, 2012; Vancouver, Weinhardt, et al., 2010; Weinhardt & Vancouver, 2012). Furthermore, discrepancies are sometimes modeled as difference functions (e.g., Vancouver, 2008; Weinhardt & Vancouver, 2012); for example:

$$\text{Strain}_t = \int (\text{perceptions} - \text{desires}) dt \quad (3)$$

However, difference functions are inconsistent with control theory principles of comparator functions (Vancouver, 2008), and the functions should instead be contingent on the desire or goal of interest (Edwards, 1992). In other words, functions may not universally apply to all values of inputs and outputs. Rather, modelers may specify discrepancies as either optima (i.e., equivalent perceptions and desires, or “desires = perceptions,” is conceptually ideal), maxima (i.e., “perceptions > desires” is ideal), or minima (i.e., “perceptions < desires” is ideal; Vancouver, 2012; Vancouver & Weinhardt, 2012). The appropriate function equation therefore depends on the theoretical relationships among variables. For example, Strain is specified as minima in Equation 3; when perceived demands are higher than desired demands, the equation yields a positive value output to represent increased Strain (i.e., a nonideal outcome).

Nonetheless, Equation 3 only partially captures these variable relationships, as JD-R theory posits that excessive job demands (i.e., higher perceptions than desires) leads to strain outcomes, whereas neutral (equal perceptions and desires) or low job demands (higher desires than perceptions) do not (Bakker & Demerouti, 2017). In other words, strain refers to reductions in well-being (i.e., negative outcomes via the health impairment process; see Schaufeli & Taris, 2014), or one tail of a hypothetical well-being distribution. The implication is that strain should

only result (and therefore be passed on to subsequent functions) from positive discrepancies wherein perceptions of demands are higher than desires. In all other cases, strain should not result and impact subsequent functions. I therefore specified the Strain function using a conditional If-Then function in the following equation (see Table 2 for the Vensim® equation code):

$$\begin{aligned} \text{if (perceptions - desires) > 0 then,} \quad \text{Strain}_t &= \int (\text{perceptions} - \text{desires}) dt & (4) \\ \text{else,} \quad \text{Strain} &= 0 \end{aligned}$$

Although this equation addressed the initial issue of when strain should result, one final addition better replicated the self-undermining proposition along with JD-R principles.

Specifically, another proposition of JD-R theory postulates that job resources and/or personal resources may buffer the negative effects of demands on strain outcomes (Bakker & Demerouti, 2017). This principle is widely supported in research, and the moderation effect is typically conceptualized as a statistical interaction (Bakker & Demerouti, 2017; Bakker, Demerouti, & Euwema, 2005). To represent this relationship, I therefore added resources as an exogenous variable to the model with an initial value of 1 (to represent no moderating effect in the initial simulation) and modified the Strain equation to be the following:

$$\begin{aligned} \text{if (perceptions - desires) > 0 then,} \quad \text{Strain}_t &= \int ((\text{perceptions} - \text{desires}) \times \text{resources}) dt & (5) \\ \text{else,} \quad \text{Strain} &= 0 \end{aligned}$$

Performance. The next function was performance, which only received one arrow and involved several assumptions to specify. Although one could argue that performance is a dynamic variable, I specified it as a state endogenous variable given that it varies across contexts (e.g., typical performance vs. maximal performance; Sackett, Zedeck, & Fogli, 1988; Schmitt,

Cortina, Ingerick, & Wiechmann, 2003). For example, in academic settings individuals may exhibit high performance at critical points in time (e.g., paper assignments, final exams, etc.) that is abstrusely related to typical performance at less critical points during the semester. The ambiguity of past performance's effect on future performance may at least partially dissipate when other factors are considered with temporal factors, such as personality variables (e.g., conscientiousness; Hurtz & Donovan, 2000), interests (Rounds & Su, 2014), or performance feedback (DeNisi & Sonesh, 2011). Nonetheless, I retained performance as a state variable to elicit a simple model without extraneous assumptions about individual differences that may influence dynamic academic performance outcomes.

In the academic context of this study, cognitive ability (more broadly, “general mental ability” or GMA; Schmidt & Hunter, 2004) was a relevant variable for a simple assumption about the effect of strain on performance. Research has supported both positive associations between cognitive ability and academic performance (Brown, Tramayne, Hoxha, Telander, Fan, & Lent, 2008; Coyle, Purcell, & Snyder, 2013; Keefer, 1969; Schult & Sparfeldt, 2016) and negative associations between strain and academic performance (Ahrberg, Dresler, Niedermaier, Steiger, & Genzel, 2012; Frazier et al., 2018; Keogh, Bond, & Flaxman, 2006; Kiselica, Baker, Thomas & Reedy, 1994; Stewart, Lam, Betson, Wong, & Wong, 1999), including research based in JD-R theory (Pluut et al., 2015). Researchers also generally support the notion that cognitive ability and cognitive functioning are related to both health and performance in work contexts (e.g., Fisher, Chaffee, Tetrick, Davolos, & Potter, 2017). Furthermore, cognitive ability predicts performance in a wide variety of jobs and occupations (Schmidt & Hunter, 1998) and is considered among the most valid predictors of job performance (Hunter & Hunter, 1984).

Although the explicit combined effect of strain and cognitive ability on academic performance is relatively unstudied, including cognitive ability in the model assumed that variance in cognitive ability may in some way alter the relationship between strain and performance. Moreover, an additive effect would assume that cognitive ability uniformly impacts the strain-performance relationship, whereas a multiplicative effect would imply that the effect of cognitive ability varies as strain varies. The latter required more convoluted assumptions, given that the precise nature of the interaction would be complex. For example, heightened or chronic strain may reduce cognitive functioning in individuals (Elovainio et al., 2009), and cognitive functioning is impacted by individual factors such as age and health (Fisher et al., 2017), so the interaction specifications would likely be contingent on other temporal and individual difference factors. Thus, for parsimony, I specified an additive effect with the following equation with an initial value of 0 that represented the natural origin:

$$\text{performance} = -\text{Strain} + \text{cognitive ability} \quad (6)$$

In sensitivity analyses, positive cognitive ability values would represent higher performance among high-GMA individuals than low-GMA individuals. Additionally, the negative Strain value indicated that performance decreases as Strain increases, and the additive effect specified the simple relationship wherein individual GMA differences may result in higher or lower performance values over time.

Self-undermining behaviors. Next, the Self-Undermining Behaviors function also necessitated several assumptions to specify the impact of Strain and, subsequently, the output the function would pass on to Demands. First, I conceptualized Self-Undermining Behaviors as a dynamic variable to most appropriately model the proposed loss spiral in JD-R theory. Second, the relationships among strain, self-undermining behaviors, and demands have not yet been

assessed in published research, and current JD-R theory correspondingly only explains the anticipated relationships with the postulate that they are positive and augment over time. I therefore reviewed other theoretical and empirical principles to determine and specify the function. Third, in the review and specification, I also aimed to address the research question regarding the impact of individuals' behavioral awareness on the strength, speed, and/or duration of the loss spiral.

Although I-O and OHP researchers have empirically assessed the relationships between strain and behavior, the focus has typically been on behaviors other than self-undermining. For example, researchers have studied the relationships between strain and behaviors such as counterproductive work behaviors (e.g., Krischer, Penney, & Hunter, 2010; Welbourne & Sariol, 2017), organizational citizenship behaviors (e.g., Ford, Wang, Jin, & Eisenberger, 2018; Mao, Chang, Johnson, & Sun, 2019), and employee turnover and withdrawal behaviors (e.g., Kelloway, Gottlieb, & Barham, 1999; Podsakoff, LePine, & LePine, 2007). In addition to unclear implications for the Self-Undermining Behaviors function, a relevant limitation of these studies is an inconsistent conceptualization of behaviors as either an outcome of strain or as an intermediary variable on the stressor-strain relationship. Thus, other theory informed the Self-Undermining Behaviors function.

Specifically, the theory of planned behavior (TPB; Ajzen, 1985; 1991; 2005) is one of most influential and frequently-referenced models to predict human behavior (Ajzen, 2011). The theory posits that behavior is anteceded by individuals' behavioral intention, which is influenced by one's attitudes (i.e., subjective evaluations or appraisals of the behavior's favorability), subjective norms (perceptions of social pressure to perform the behavior), and perceived behavioral control (perceptions of one's ability to perform the

behavior; Ajzen, 1991). Moreover, attitudes are purportedly influenced by *behavioral beliefs* about the consequences of behavior, just as subjective norms are influenced by *normative beliefs* about others' approval or disapproval of the behavior and control perceptions are influenced by *control beliefs* in facilitating or inhibiting factors (e.g., skills, abilities, and available resources) that affect performance (Ajzen & Cote, 2008). The TPB framework also postulates that intention is derived from the total set of accessible behavioral, normative, and control beliefs.

Although TPB principles have not been explicitly incorporated into the JD-R model, the TPB nonetheless has informed many researchers' conceptualizations, predictions, and results. For example, JD-R researchers have used the TPB to support and/or explain ways to predict and practically encourage job crafting (Tims, Bakker, & Derks, 2015); associations between turnover intentions and behaviors (Rudman, Gustavsson, & Hultell, 2014); the need to assess the interrelationships among job demands, control, and support (Luchman & González-Morales, 2013); buffer effects of group cohesion (Urien, Osca, & García-Salmones, 2017); associations between attitudes toward organizational change and employee behaviors (Petrou, Demerouti, & Schaufeli, 2015); and the conceptualization of retirement as a decision-making process (Schreurs, De Cuyper, van Emmerik, Notelaers, & de Witte, 2011; Wang & Shultz, 2010). Thus, the TPB is clearly relevant and influential to JD-R research. I therefore added the exogenous variable "intention" to the visual model to include with Strain in the Self-Undermining Behaviors function.

Research has suggested that job strain and TPB principles conjunctively influence individuals' behavior, although the nature of the effects is unclear (Payne, Jones, & Harris, 2002). An additive relationship between Strain and intention would indicate that intention's

influence is equivalent across all levels of Strain, which was conceptually implausible. For example, Payne et al. suggested that job strain may not directly affect behavioral intention but may disrupt individuals' volition and ability to perform the intended behavior. Their interpretation aligns with the TPB postulate that intention is expressed as behavior only when the behavior is under volitional control (i.e., when the person can decide to enact the behavior at will; Ajzen, 1991). Strain is typically conceptualized as exhaustion, health detriments, anxiety, and/or other negative physiological and psychological symptoms (Bakker & Demerouti, 2017), all of which could potentially disrupt one's ability to willingly behave in a certain manner (i.e., one's volitional control).

Furthermore, the TPB posits that intention is influenced by one's accessible behavioral, normative, and control beliefs (Ajzen, 1991). In states of excessive strain and depleted personal resources, behavioral intention may change in an undesirable manner due to inaccessible and/or altered beliefs. Thus, the intentional factor is likely non-uniform across all levels of strain. Specifically, if individuals do not intend to behave in self-undermining ways, the intention-behavior effect may be attenuated in cases of excessive strain. This suggested an interaction effect of Strain and intention, as specified in the following equation:

$$\text{Self-Undermining Behaviors}_t = \int (\text{Strain} \times \text{intention}) dt \quad (7)$$

Related to the interaction between Strain and intention, TPB principles also informed an initial speculation about the impact of behavioral awareness on the loss spiral. Specifically, a change or negation in loss spiral processes would involve individuals that decrease or stop behaving self-underminingly and instead shift to more desirable behaviors. Per TPB principles, this could manifest in behaviorally aware individuals due to their behavioral beliefs (e.g., that the consequences of self-undermining behaviors are detrimental), control beliefs (that they can

behave differently), and/or normative beliefs (that others would disapprove of their behavior). Conversely, if individuals are aware of their self-undermining tendencies but fail to change behaviors (i.e., perpetuating the spiral), this could relate to alternative beliefs about their behavior (e.g., that the consequences will not be detrimental), their control (that one cannot change, or that one's abilities will still enable high performance), and/or social norms (that one's peers behave similarly).

In support of these assumptions, research has suggested that students' beliefs can influence academic behavior intentions, such as intentions to collaborate in group projects (Cheng & Chu, 2016), to complete the school year (Davis, Saunders, Johnson, Miller-Cribbs, Williams, & Wexler, 2003), to graduate (Sutter & Paulson, 2017), and to use mobile learning services (Sabah, 2016). Nonetheless, the intention-behavior relationship among students is less clear. Although research has supported the connection between intention and academic achievement or performance (e.g., Ajzen & Madden, 1986; Phillips, Abraham, & Bond, 2003) the self-undermining behaviors construct is conceptually distinct from performance in the current JD-R model. More generally, although several meta-analyses have reported that intentions are strong predictors of behaviors ($.63 < R^2 < .71$; see Ajzen & Cote, 2008), other meta-analyses have suggested that the relationship is weaker ($R^2 = .28$) and likely moderated by other factors (e.g., cognitive and personality variables; Sheeran, Webb, & Gollwitzer, 2005).

Altogether, TPB principles may be contextually extrapolated to suggest circumstances in which students' intentions alter or break the loss spiral in JD-R theory. Nonetheless, the presence and/or magnitude of the effect would likely vary between individuals. Although there are limitations associated with these assumptions, such as the mixed effects in research literature and potentially confounding effects from other individual differences, I retained intentions in the

model to provide an initial investigation into the effect of awareness (i.e., in the broader context of cognitive processes of the TPB) in a simple model.

Demands. The final variable was Demands, which I conceptualized as a dynamic variable to model the self-undermining proposition. This relied on the self-undermining proposition's general assumption that demands change as a function of individuals' behaviors. Nonetheless, demands in this study were school characteristics and therefore would vary as a function of the environment. For example, an instructor may unexpectedly assign new tasks to students, thereby increasing demands. In sensitivity analyses, environmental changes in demands could be simulated by adding "step changes" in Vensim® that alter values at certain time steps as specified by the modeler.

As discussed previously in this section, current research has not investigated the relationships among variables in the self-undermining proposition, including the relationship between behaviors and demands. Rather, the JD-R model only states that the relationship is positive and may strengthen with time (Bakker & Demerouti, 2017). I therefore included the exogenous demands responsiveness variable to represent the rate of the impact of self-undermining behaviors on demands. A value of 1 would represent instantaneous impacts of behavior on the environment (Vancouver & Weinhardt, 2012), indicating in this context that students' self-undermining behaviors would immediately increase their school demands. This was conceptually implausible, and I therefore chose a fraction (0.1) to represent the lagged effect of self-undermining behaviors on demands. Finally, I specified the initial value of Demands function as the exogenous initial demands variable and assigned the following equation:

$$\text{Demands}_t = \int (\text{Self-Undermining Behaviors} \times \text{demands responsiveness}) dt \quad (8)$$

Equation 8 therefore stipulated that Demands is a function of both time (i.e., prior Demands values) and Self-Undermining Behaviors as qualified by the responsiveness of demands to individuals' behavior.

Step Four: Model Evaluation and Results

I next evaluated the computational model by comparing the model to theoretical predictions (i.e., did it convey what was expected?; Vancouver et al., 2005; Vancouver & Weinhardt, 2012). At this stage I assessed graphs in Vensim® and used sensitivity analysis (Davis et al., 2007) to determine if the model capably portrayed the self-undermining proposition as conceptualized in JD-R theory. In initial simulations, the current model yielded a positive feedback loop that aligned with the tenet of loss spirals in the self-undermining proposition. In other words, when not considering the impact of appraisal, resources, and intentions, the model showed that individuals experience heightened strain, which thereby led to increases in self-undermining behaviors, which increased demands and demands perceptions to further the positive feedback loop and strengthen the relationships over time. See Figure 5 for a graph of the initial model output.

An immediately apparent issue was that the values of Self-Undermining Behaviors rose much faster than those for any other variables in the model. Although this issue could be alleviated by altering the initial values of intentions (e.g., from 1 to 0.5), this change in the current model conceptualization would imply that all individuals are acting to reduce self-undermining behaviors. To avoid this assumption, I therefore changed the Self-Undermining Behaviors function to portray a diminished effect of Strain (similar to a modification by Vancouver & Weinhardt, 2012). Specifically, I respecified the equation as follows:

$$\text{Self-Undermining Behaviors}_{t=} \int \left(\frac{\text{Strain} \times \text{intention}}{2} \right) dt \quad (9)$$

Another issue in the initial model output was that the performance trajectory represented the inverse of Strain. That is, in Figure 5, performance decreased at the exact rate that Strain increased, which would essentially represent a perfectly negative correlation (i.e., $r = -1.0$). This is implausible, and I alleviated the issue similar to Equation 9 by respecifying the performance equation to be the following:

$$\text{performance} = \frac{-\text{Strain} + \text{cognitive ability}}{2} \quad (10)$$

When altering exogenous variables in sensitivity analyses, I also identified a minor misspecification that yielded counterintuitive results. Specifically, the initial value for resources was specified at 1 to represent no initial interaction effect on the Strain function. However, the Strain equation was specified such that increases in resources (e.g., from 1 to 1.1) augmented the loss spiral. To correct this error, I respecified the Strain equation as follows:

$$\begin{aligned} \text{if (perceptions - desires) > 0 then,} \quad \text{Strain}_t &= \int \left((\text{perceptions} - \text{desires}) \times \frac{1}{\text{resources}} \right) dt \quad (11) \\ \text{else,} \quad \text{Strain} &= 0 \end{aligned}$$

After this change, the model yielded similar initial output when resources = 1, and better portrayed the buffer effect when resources increased. This specification did suggest diminishing returns of resources (i.e., a change from 1 to 1.1 attenuates Strain output to a greater extent than a change from 1.1 to 1.2), but the precise nature of this interaction effect is unspecified in current literature and I retained the change to reflect the general buffering relationship in the current JD-R model (see Bakker & Demerouti, 2017). Figure 6 shows a graph of the model output when these modifications were included.

At this juncture, it is important to reiterate that these changes were based in general, rather than precise, assumptions about the relationships among variables in the model. In other

words, the purpose of these respecifications was to demonstrate a computational model that was more theoretically and empirically compatible with JD-R theory and research, or one that portrays the general relationships among variables in the JD-R model, rather than a model that shows exact or precise relationships. Sensitivity analyses provided further insight of the model depiction of these general relationships via changes in variable trajectories as I varied exogenous variables' initial values. For example, Figure 7 shows changes in the simulation output when the initial value of resources was changed to 0.5 (low resources) and 1.5 (high resources) from 1 (baseline).

In summary, the computational model in this study did generally depict the theoretical premises of the self-undermining proposition. Although there were issues in the model, such as a perpetual positive feedback loop of increasing variable trajectories, fully interpreting the model in this research context entailed comparing the model results to those of the longitudinal study. I next describe the methods and results of the longitudinal study prior to interpreting the integrative results.

Methods – Longitudinal Study

Participants and Procedure

The study utilized a repeated measures longitudinal survey design with an undergraduate student sample ($N = 599$) over three time points during the spring 2019 academic semester. Participants from a large Western U.S. university (hereby referred to as “Western” participants; $n = 525$) and a large Southern U.S. university (“Southern” participants; $n = 74$) completed three 10-15 minute online Qualtrics surveys with approximately two week intervals between surveys (see Table 3 for the data collection schedule). Participants in both samples were recruited online through study descriptions posted on research portal websites at each university. Western

participants were also recruited via both in-person announcements (i.e., projected slides and brief discussion in face-to-face courses) and electronic communication (learning management system posts). To participate in the study, students were required to be at least 18 years old and currently enrolled at their university. In the initial sample ($N = 599$), 74% completed the survey at Time 1 (T1; $n = 443$), 68% participated at T2 ($n = 408$), and 62% participated at T3 ($n = 371$). Additionally, 43% of participants completed all three surveys ($n = 260$), 17% completed only two surveys ($n = 103$), and 39% completed only one survey ($n = 236$).

In the process of data cleaning (described further in the Results section), 170 participants were removed from the initial sample for inattentive responding, missing data, and/or outliers. The final sample analyzed in hypothesis tests ($n = 429$) therefore retained participants from both the Western ($n = 380$) and Southern ($n = 49$) universities. Of the 429 final participants, 80% completed the T1 survey ($n = 341$), 66% participated at T2 ($n = 283$), and 63% participated at T3 ($n = 271$). Forty-eight percent of the final sample completed all three surveys ($n = 204$), 14% completed two surveys ($n = 58$), and 39% completed only one survey ($n = 167$). Demographic information was collected in the T1 survey (described further in the Measures section); thus, the following demographic results only include the 341 participants that responded to the T1 survey.

The final T1 survey participants were predominantly female ($n = 256$; males: $n = 83$; preferred not to disclose: $n = 2$) and their average age was 20.92 years ($SD = 3.97$). T1 participants were asked to “mark all [categories of race/ethnicity] that apply” and identified themselves as White ($n = 266$), Hispanic/Latino ($n = 52$), Asian/Asian-American ($n = 24$), Black ($n = 19$), Native American/Alaska Native ($n = 6$), and two or more races ($n = 8$). The final T1 sample was primarily full-time students ($n = 330$; part-time: $n = 11$), and 29% were freshman ($n = 29$), 25% were sophomores ($n = 84$), 24% were juniors ($n = 103$), 16% were seniors

($n = 53$), and 0.5% marked “other” class standing descriptions (not described here to avoid disclosing identifying information; $n = 2$). T1 participants’ majors or areas of study included psychology ($n = 142$; 42%), business ($n = 36$; 11%), health and exercise science ($n = 17$; 5%), undecided/undeclared ($n = 17$; 5%), sociology ($n = 12$; 4%), social work ($n = 11$; 3%), and human development and family studies ($n = 10$; 3%). All other categories of majors were represented by ten or fewer participants. Finally, 59% of T1 respondents currently had at least one job ($n = 202$), and 41% were not employed or working for pay ($n = 139$). Participants who held jobs indicated that they worked an average of 19.4 hours in a typical week ($SD = 12.5$).

Time lags. The two week intervals in the data collection schedule (see Table 3) were chosen to capture fluctuations in academic demands over the latter part of the academic semester, as well as the effect of these fluctuations on individuals’ strain, behaviors, and performance outcomes. Many JD-R studies in work contexts involve time lags of months to years (Bakker & Demerouti, 2017), which was inappropriate for this academic research context. Moreover, I chose biweekly intervals given that researchers have argued for daily or weekly processes in JD-R model variable relationships (e.g., Bakker & Costa, 2014), and that academic demands likely fluctuate in short-term intervals (i.e., due to assignments, exams, and other responsibilities over weeks in the semester).

Efforts to reduce attrition. The design included several methodological components to reduce survey attrition that were informed by personal communications with three experienced longitudinal researchers (K. Henry, personal communication, January 30, 2019; T. Tran, personal communication, January 30, 2019; N. Yetz, personal communication, January 29, 2019) and by literature with recommendations on best practices in longitudinal research (e.g., Lynn, 2009; Ployhart & Vandenberg, 2010). First, although I could not financially compensate

participants, all participants received some form of course credits for participating in the study survey. In the Western sample, 135 participants completed the surveys for course extra credit (i.e., “extra credit participants”) and all other participants completed the surveys to receive credit to fulfill course research participation requirements (“research pool participants”). In the Southern university sample, all participants were research pool participants. Western research pool participants were required to complete all three surveys to receive credit. All Western extra credit participants and Southern research pool participants were granted credit on a case-by-case basis (i.e., a specified number of credits per survey). Second, in both samples, the survey recruitment materials and informed consent forms included information to build rapport with participants and explain the importance, purpose, and goals of the research; the longitudinal study design; and the role that they would play in our study as participants. Third, I sent reminder emails to all participants on survey start dates and midway through the data collection period for each survey (see Table 3). Finally, in all communications with participants (i.e., recruitment materials, research pool study postings, and reminder emails) I included information on the deadlines for survey participation and the number and dates of remaining future surveys.

Measures

Prior to data collection, the online Qualtrics survey was piloted by five subject matter experts (SMEs) with prior experience in online survey research. Surveys at time points one through three (T1-T3) included questions about participants’ academic demands, strain, self-undermining behaviors, and performance. Additionally, the T1 survey included questions to acquire participants’ informed consent, demographics, enrollment status, area of study, and employment (see Appendix A). T1 survey items were used as baseline measures and asked students to think about their general perceptions and experiences when responding to survey

items at that time. Surveys at T2 and T3 prompted students to think about the past two weeks (i.e., the time since the prior survey) to respond to all items; the T2 and T3 items were modified to the past tense for clarity (e.g., “I feel” was revised to “I felt”). T2 and T3 surveys also included qualifier questions to identify students’ whose course schedules had changed since the preceding survey (Appendix B).

I next describe the scales for all study variables. Unless otherwise stated, participants responded to all scales using a five-point Likert scale ranging from “Strongly Disagree” to “Strongly Agree”.

Demands. Academic demands were measured using a modified version of the five-item Quantitative Workload Inventory (QWI; Spector & Jex, 1998). JD-R researchers have used the QWI to assess demands in many contexts, such as in predicting strain and well-being outcomes and/or in longitudinal research (e.g., Baka, 2015; Boyd, 2010; Kinnunen, Feldt, de Bloom, & Korpela, 2015; Lu, Chang, Kao, & Cooper, 2015). Although other measures of demands are available in research literature, many alternatives are either proprietary (e.g., the Job Content Questionnaire; Karasek, Brisson, Kawakami, Houtman, Bongers, & Amick, 1998), lack validity evidence (see Boyd, 2010, and Spector & Jex, 1998), and/or have not been fully reported in published research (e.g., Bakker, Demerouti, Taris, Schaufeli, & Schreurs, 2003). Furthermore, as opposed to qualitative measures of the subjective difficulty of work tasks, the QWI was designed to assess the amount or quantity of work in a job. In support of the QWI, a meta-analysis by Spector and Jex described the early development and use of the inventory in 15 studies (average $\alpha = .82$). Spector and Jex also reported supportive validity evidence for the scale, such as positive relationships with strain outcomes and turnover intentions and negative relationships with job satisfaction and job performance. In this study, participants responded to

five items that were modified to ask about students' schoolwork, such as "How often does your schoolwork require to you to work very fast?" and "How often is there a great deal to be done?". All items were rated on a Likert scale ranging from "Less than once per month or never" to "Several times per day." See Appendix C for the full demands scale.

Strain. Strain was assessed with a modified version of the eight-item exhaustion subscale of the Oldenburg Burnout Inventory (OLBI; Demerouti, Bakker, Vardakou, & Kantas, 2003; Demerouti, Mostert, & Bakker, 2010). The OLBI is widely supported as a measure of burnout with two factors (i.e., exhaustion and disengagement; Demerouti et al., 2003; Reis, Xanthopoulou, & Tsaousis, 2015). Research has supported the use of exhaustion as a measure of strain in the JD-R model (e.g., Bakker et al., 2004; Demerouti et al., 2001; Demerouti & Bakker, 2008), as well as the reliability of the exhaustion subscale in work contexts (e.g., Demerouti et al., 2003, $\alpha = .73$; Demerouti et al., 2010, $\alpha = .78$) and in academic contexts (e.g., Campos, Zucoloto, Bonafé, Jordani, & Maroco, 2011, $\alpha = .76$; Reis et al., 2015, $\omega = .97$ and $.99$; Timms, Graham, & Cottrell, 2007, $\alpha = .81$). All scale items were modified to ask about students' experiences at school rather than work. For example, the original scale item "There are days when I feel tired before I arrive at work" was revised to "There are days when I feel tired before I begin my studies." See Appendix D for the exhaustion scale.

Self-undermining. Self-undermining behaviors were measured using a newly developed scale that was adapted and expanded from the original six-item scale developed by Bakker and Wang (2016) as reported by Bakker (2016). In a study of the validity of the original construct and scale, Bakker and Wang found support for the single-factor model structure of the scale using seven samples from China, Chile, the United States, Romania, and the Netherlands ($.70 < \alpha < .88$ across samples). Factor loadings for the six items ranged from $.54$ to $.79$. In support of the

criterion-related validity of the construct and scale, Bakker and Wang found that scale scores positively related to job demands (work pressure, $r = .25, p < .001$; emotional demands, $r = .39, p < .001$) and exhaustion ($r = .24, p < .001$). Moreover, in the U.S. sample, scale scores positively related to burnout ($r = .51, p < .001$). The original six scale items are: “I make mistakes,” “I admit that I create stress at work,” “I create confusion when I communicate with others at work,” “I create a backlog in my tasks,” “I run into problems at work,” and “I admit that I create conflicts.”

In this study I adapted and expanded Bakker and Wang’s (2016) scale to measure academic- or school-related self-undermining behaviors. Specifically, I defined the construct as “behaviors of students under stress that can impair their own functioning and worsen their working conditions; i.e., student behaviors that create obstacles that may undermine or hinder the individual’s academic performance” (adapted from Bakker, 2016). In consideration of this definition, I developed 34 survey items after a literature review on academic performance (i.e., to ensure the constructs were distinct) and on scale development and item writing (A. M. Gibbons, personal communication, February 4, 2014; DeVellis, 2012). Prior to data collection, the 34 survey items were reviewed by 12 SMEs that had completed a graduate-level course in psychological testing and measurement. SMEs were prompted to review each item and respond to the following three questions: “This item indicates the extent to which a student did or did not engage in self-undermining behaviors,” “This item is clear and concise,” and “This item is easy to rate from a student’s perspective.” SMEs responded to each question with on a 1-7 Likert scale (“Strongly Disagree” to “Strongly Agree”) and could also provide additional comments about each survey item. After reviewing the quantitative and qualitative data for all survey items, I removed five items from the measure that SMEs deemed as invalid (e.g., due to irrelevant

content or failure to represent the construct domain). Thus, the final scale in the survey included 29 items to measure students' perceptions of self-undermining behaviors. After data cleaning and factor analyses, the final scale retained for hypothesis tests included five items and demonstrated acceptable reliability at each time point (T1: $\omega = .82$; T2: $\omega = .85$; T3: $\omega = .83$; reliability calculations are further described in the Results section). See Appendix E for the full 29-item scale and the five final scale items.

Performance. Recent research suggested that students are overconfident in self-predictions of grades (e.g., Magnus & Peresetsky, 2017; Serra & DeMarree, 2016), and I therefore measured academic performance via self-reported grade and GPA by using and adapting a single GPA item from prior research on student learning strategies (Morehead, Rhodes, & DeLozier, 2015; M. G. Rhodes, personal communication, January 25, 2019). To capture self-reports of current course grade and GPA, I informed participants that they would be asked about their grades at all timepoints. Specifically, I included text in all email communications and survey instructions to describe that the survey would ask students about their grades and recommend that they look up their grades prior to beginning the surveys. Additionally, communications with the Western sample also included instructions about how students could look up grades and GPA in the Western university's online system. In the survey, students were first asked "For what course are you participating in this study?" to provide piped text for the follow-up question, "What is your current grade in [the course]?". The GPA item was "What is your current GPA for the spring 2019 semester?" See Appendix F for the response options on academic performance items.

Results – Longitudinal Study

Data Screening

Prior to analyses I conducted multiple screening procedures to ensure data quality, including data cleaning and assessments of missing data, inattentive responding, outliers, assumptions, internal consistency, test-retest reliability, and factor structure (Kline, 2011; Tabachnick & Fidell, 2013).

Data cleaning. I assessed for data accuracy within and between timepoints and found no discrepancies in survey items, values, variable names, labels, levels, and types. All items were reverse coded as specified in the Appendices. I also assessed unique identifier codes for accuracy and resolved inconsistencies by capitalizing all identifier codes (i.e., to optimally match cases across timepoints) and then merged the datasets using SPSS (IBM Corp., 2012). The initial unmerged datasets included 604 total cases; five of these cases were removed during merging via listwise deletion due to either duplicate responses (e.g., participants opened the survey on two occasions, but only responded to unique code-creation items on the first occasion) or nonresponses. In instances of the former, I removed participants' incomplete cases and retained complete cases. In instances of the latter, I removed cases of nonrespondents with person-level (e.g., providing no responses) or near person-level missingness (e.g., responding to only one scale at one timepoint), given that I had no information to improve estimation and reduce the bias and error associated with nonrespondent missing data (Newman, 2014). Thus, the final dataset for further data screening included the total participants reported in the Methods section ($N = 599$).

Missing data. I used the Missing Values Analysis (MVA) procedure of SPSS to assess missing value patterns among the data. I specified the MVA to (a) request separate variance

t-tests ($\alpha = .05$) for variables missing at least five percent of data to assess if missingness was related to other study variables, and (b) use expectation-maximization (EM) estimation to request correlations and Little's MCAR test to assess if missing data patterns were missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR; IBM Corp., 2012.; Tabachnick & Fidell, 2013). MVA results in the merged dataset suggested the data were MCAR, as indicated by the non-significant Little's test ($\chi^2(7579) = 7616.56, p = .378$).

Furthermore, most missing data were due to nonparticipation in early surveys or attrition in later surveys. Within each timepoint, missingness occurred in less than 5% of all study variables. Such instances of low missingness (i.e., < 5%) are typically less problematic and will yield similar results regardless of the procedure implemented by the researcher (Kline, 2011; Tabachnick & Fidell, 2013). I therefore opted to use Full Information Maximum Likelihood (FIML) parameter estimation from the incomplete data matrix for hypothesis tests, given that it unbiased under MCAR assumptions and outperforms other methods (e.g., listwise deletion) that may produce parameter errors (Newman, 2003; 2014).

Inattentive responding and outliers. I assessed for inattentive responding (also referred to as careless responding) and outliers through several integrated methods. Although there are many resources in the literature for assessing inattentive responding (e.g., Curran, 2016; DeSimone, Harms, & DeSimone, 2015; Dunn, Heggestad, Shanock, & Theilgard, 2016; Huang, Curran, Keeney, Poposki, & DeShon, 2012; Maniaci & Rogge, 2014; Meade & Craig, 2012), the available information is often conflicting and utilizes arbitrary cutoffs to identify careless responders (Kraiger, McGonagle, & Sanchez, 2019). I therefore used several methods that together entailed a "multiple hurdles approach" (Curran, 2016, p. 16), including observational methods and assessments of invariance, consistency, and outliers.

I assessed inattentive responding through three integrated methods: participant response times, invariability in responses (also known as “long-string analysis” or “response pattern indices”; Curran, 2016; Huang et al., 2012), and person-total correlations (Curran, 2016). Regarding the former, researchers have recommended specific cut scores for response time (such as 2 seconds an item; Huang et al., 2012) but concrete rules may not apply to all contexts, and I therefore carefully applied subjective cut scores (Curran, 2016). In this study, Huang et al.’s (2012) recommendation would yield cut times of approximately 198 seconds at T1 and 166 seconds at T2 and T3 (disregarding time spent reading instructions or loading pages). I deemed these cut scores as contextually inappropriate and too conservative, echoing Curran’s concerns. I instead assessed the median, range, and values of survey response times in conjunction with long-string analysis, a method to remove responders with consistently invariable responses (e.g., selecting a “5” on a 1-5 scale consecutively for at least half of the scale items; Curran, 2016). I visually assessed response invariance with conditional formatting tools in a spreadsheet of the dataset sorted by ascending response times among participants. The integrative method revealed numerous participants with response patterns that were invariant, temporally unreasonable (i.e., questionably fast or slow), or a combination of the two. I deemed these as indicative of inattentive responding and removed 60 participants from the dataset.

I next calculated person-total correlations to assess the patterns of each responder as compared to the expected patterns of other individuals in the data set, where negative person-total correlations indicate patterns counter to others in the sample. In other words, person-total correlations are “a measure of how consistent any given person is, relative to the expected patterns generated by all other persons” (Curran, 2016, p. 12). I calculated person-total correlations on all scale variables by saving imputed variable values via EM estimation in MVA,

transposing the imputed dataset to a person-by-item matrix, and requesting item-total correlations in SPSS reliability analyses. Given that person-total correlations are relatively novel means of detecting inattentive responding, I adopted Curran's (2016) conservative recommendation that "individuals with negative person-total correlations be considered careless/inattentive responders by this technique" (p. 13) and removed only cases with negative person-total correlations ($n = 110$).

Finally, I assessed for outliers and further assessed for inattentive responding through Mahalanobis distance (D) statistics. Specifically, I saved Mahalanobis D statistics in Mplus to analyze outliers in multivariate space via information on the distance between respondents' responses to all study items and responses of other participants (see Curran, 2016; Kline, 2011; Maesschalck, Jouan-Rimbaud, & Massart, 2000; Mahalanobis, 1936). Importantly, Mahalanobis distance is a relatively novel method of detecting careless responders and "should be used as a way to flag individuals for deeper examination, but may not yet be a clear means of eliminating careless/inattentive responders on its own" (Curran, 2016, p. 9). Therefore, I repeated the long-string analyses approach of conditional formatting in spreadsheets sorted by descending significant Mahalanobis D values to assess for identifiably different response patterns among all remaining cases. I identified no patterns among that suggested extreme outliers or inattentive responding. Furthermore, Mahalanobis D values did not correlate with response times at T1 ($r = -.068, p = .212$), T2 ($r = -.045, p = .450$), or T3 ($r = .004, p = .953$). Given these findings, I therefore did not consider any remaining cases as inattentive responders and retained all remaining participants.

Factor analyses, reliability, and assumptions. I next assessed the factor structure of the self-undermining behaviors (SUB) scale through confirmatory factor analysis (CFA). Although

the current scale was modified and expanded for an academic/school context, I attempted to replicate the unidimensional SUB factor structure identified by Bakker and Wang (2016). An initial one-factor CFA in Mplus with maximum likelihood (ML) estimation, with all T1 SUB items loading on a single factor, indicated poor model fit in the complete dataset ($\chi^2(377) = 2109.26, p = .000$; RMSEA = .12; CFI = .61; TLI = .58; SRMR = .09) per conventional fit indices (i.e., non-significant χ^2 , RMSEA < .08, CFI > 0.95, TLI > 0.95, SRMR < 0.08; Hu & Bentler, 1999). I then implemented a cross-validation strategy to finalize the SUB model (e.g., Mosier, 1951; Steger, Dik, & Duffy, 2012). Specifically, I randomly split the sample into two proportionally equivalent datasets ($n = 215$ and $n = 214$) to fit the model in one-half the sample and cross-validate the model in the other half. I conducted a single-factor CFA on the first half in Mplus with maximum likelihood (ML) estimation, with all T1 SUB items loading on a single factor. The results indicated poor model fit ($\chi^2(377) = 1277.87, p = .000$; RMSEA = .12; CFI = .61; TLI = .58; SRMR = .09). To refine the item pool, I dropped items with low factor loadings (i.e., initially loadings < .3 and then items < .6 in subsequent iterations), low or negative correlations, problematic item discrepancies (i.e., discrepancies < 0 or discrepancies > .1), high modification indices (> 15.0) and/or non-normal distributions. I also assessed item wording and content throughout the process to consider the implications or connection to the overall behavior of the model. The final model included five items (see Appendix E) and results indicated acceptable model fit in the first half of the sample ($\chi^2(5) = 13.05, p = .023$; RMSEA = .10; CFI = .97; TLI = .94; SRMR = .03) and when cross-validated in the second half ($\chi^2(5) = 10.65, p = .059$; RMSEA = .08; CFI = .98; TLI = .96; SRMR = .03). When expanded to include the full dataset, CFA results also indicated acceptable fit at T1 ($\chi^2(5) = 10.27, p = .068$; RMSEA = .06; CFI = .99; TLI = .98; SRMR = .02). Subsequent CFAs with the full dataset further indicated

acceptable fit at T2 ($\chi^2(5) = 3.83, p = .575$; RMSEA = .00; CFI = 1.00; TLI = 1.00; SRMR = .01) and at T3 ($\chi^2(5) = 7.65, p = .177$; RMSEA = .04; CFI = .99; TLI = .99; SRMR = .02). Across all time points, the factor loadings of all items were $> .6$.

I next assessed the factor structure of the demands and strain scales. Using similar criteria to the SUB scale refinement, I dropped one item from the demands scale (see Appendix C) and four items from the strain scale (Appendix D) due to poor CFA model fit and/or scale reliability across time points. The final results indicated acceptable fit for demands at T1 ($\chi^2(2) = 5.63, p = .06$; RMSEA = .00; CFI = 0.99; TLI = 0.98; SRMR = .02), T2 ($\chi^2(2) = 0.93, p = .623$; RMSEA = .00; CFI = 1.00; TLI = 1.00; SRMR = .01) and at T3 ($\chi^2(2) = 3.08, p = .215$; RMSEA = .05; CFI = 1.00; TLI = 1.00; SRMR = .01). The strain measure indicated acceptable fit at T1 ($\chi^2(2) = 3.53, p = .17$; RMSEA = .05; CFI = 1.00; TLI = 0.99; SRMR = .02), near acceptable fit at T2 ($\chi^2(2) = 10.61, p = .01$; RMSEA = .12; CFI = 0.97; TLI = 0.92; SRMR = .03) and acceptable fit at T3 ($\chi^2(2) = 5.64, p = .06$; RMSEA = .08; CFI = 0.99; TLI = 0.98; SRMR = .02).

Finally, I calculated omega (ω) and correlation coefficients to assess internal-consistency and test-retest reliability, assessed statistical assumptions, and calculated descriptive statistics for all variables. I calculated omega statistics for all scales in Mplus to provide an index for internal-consistency reliability (A. M. Gibbons, personal communication, February 27, 2014; Dunn, Baguley, & Brunsten, 2014; Raykov, 2004). Omega results indicated acceptable reliability at all time points for the SUB scale (T1: $\omega = .82$; T2: $\omega = .85$; T3: $\omega = .83$), demands scale (T1: $\omega = .86$; T2: $\omega = .89$; T3: $\omega = .91$), and strain scale (T1: $\omega = .78$; T2: $\omega = .79$; T3: $\omega = .84$). I also calculated correlations in SPSS to assess test-retest reliability across all time points (demands: $r > .709$; SUB: $r > .639$; strain: $r > .626$), calculated means and standard deviations of

study variables (Table 4), and assessed the linearity, homoscedasticity, normality, and multicollinearity of model variables (Curran, West, & Finch, 1996; Tabachnick & Fidell, 2013). These assumptions were confirmed for all variables but the observed performance variables (i.e., current semester GPA and course grade), which did not significantly correlate to the demands and strain variables in the study ($-.097 < r < .066, p > .05$; Table 4) excepting of the correlation between T3 GPA and T1 demands ($r = -.138; p = .043$). Interestingly, both GPA and course grade did significantly relate to self-undermining behaviors across all time points ($-.339 < r < -.150$; Table 4). This suggested potential issues in hypothesis tests, as there would be no association between the exogenous strain variables and the endogenous performance variables in the structural model (see Kline, 2012). I proceeded with the longitudinal analyses in consideration of this finding.

Longitudinal Analyses

I used two statistical techniques with the longitudinal data to test the self-undermining proposition. First, I used Mplus (Muthén & Muthén, 1998–2017) to conduct cross-lagged panel analyses with a series of nested structural equation models to test the effects of the study variables over time. Second, I used SPSS (IBM Corp., 2012) to conduct a repeated measures multivariate analyses of variance (i.e., RM MANOVA) to assess for differences and trends in the variables across time points. These two techniques aligned with the two conditions necessary to confirm the self-undermining proposition and other loss or gain spirals (see Salanova, Schaufeli, Xanthopoulou, & Bakker, 2010); namely, to demonstrate reciprocal causal relationships between study variables and increases in loss over time. The results informed Hypotheses 1-4 that demands influence future strain (H1), strain influences future self-undermining behaviors (H2), self-undermining behaviors influence future demands (H3), and that strain influences future

performance (H4). The effects of H1-H3 were all expected to be positive, whereas the effects of H4 were predicted to be negative. I next describe the procedure for each analysis.

Cross-lagged analyses. Cross-lagged panel analysis is a method used to assess the directional effects or relationships between variables over time (Kearney, 2018; Kenny, 1975). The method has been used in studies assessing gain and loss spirals, including research that provided early evidence for the self-undermining proposition (e.g., Demerouti et al., 2009; Demerouti et al., 2004; Hakanen et al., 2008). In this study I conducted a full panel design and measured explanatory and outcome variables at each time point to test the lagged causal, reversed causal, and reciprocal effects (Taris & Kompier, 2014). Specifically, I tested four models in this study with the following paths to stipulate the self-undermining proposition:

1. Model 1 (M1): I first assessed a baseline model (see Figure 8) with only the synchronous correlations (i.e., correlations of variables within timepoints) and autoregressive paths (paths of repeated measures between timepoints) to demonstrate the stability of individual differences between time points, where large coefficients would indicate that the individuals' relative order or standings on the construct remained relatively consistent over time (Pitts, West, & Tein, 1996; Selig & Little, 2012). Models 2 through 4 were identical to M1 with the addition of specified lagged structural paths.
2. Model 2 (M2): I next assessed a causal model (see Figure 9) in which explanatory variables exhibited lagged effects on outcome variables. M2 included additional paths from T1 strain to performance, self-undermining behaviors, and demands at T2 and T3; from T2 strain to performance, self-undermining behaviors, and demands at T3;

- from T1 self-undermining behaviors to T2 and T3 demands; and from T2 self-undermining behaviors to T3 demands.
3. Model 3 (M3): M3 was a reversed causal model (see Figure 10) in which outcome variables exhibited lagged effects on explanatory variables (i.e., the inverse of M2). M2 was identical to M1 with additional paths from T1 demands to T2 and self-undermining behaviors and strain at T3; from T2 demands to self-undermining behaviors and strain at T3; from T1 self-undermining behaviors to T2 and T3 strain; from T1 strain to T2 and T3 performance; and from T2 strain to T3 performance.
 4. Model 4 (M4): Finally, M4 was a reciprocal model (see Figure 11) with both causal and reversed causal effects. M4 therefore was identical to M1 with all paths from both M2 and M3 included in the model. Significant path coefficients in M4 would indicate cross-lagged effects.

Identifying and interpreting the models involved several a priori assumptions and criteria for model evaluation. First, to account for systematic method variance, in all tests I allowed the measurement errors of individual items to covary with themselves over time (Pitts et al., 1996). For example, I specified a covariance term of the measurement error of Time 1 (T1) strain item 1 with the measurement error of strain item 1 at both T2 and T3 (and, similarly, a covariance term between item 1 measurement error at T2 and T3). Second, I also assumed stationarity (i.e., invariance over time) and constrained factor loadings of items to be equal across time points (see Demerouti et al., 2009; Pitts et al., 1996; Zapf et al., 1996). Third, I evaluated fit indices for each model using Hu and Bentler's (1999) recommended criteria, including root mean square error of approximation (RMSEA) < .06, standardized root mean square residual (SRMR) < .08, confirmatory fit index (CFI) > .95, and Tucker-Lewis Index (TLI) > .95. I also evaluated the chi-

square (χ^2) test of model fit for each model, where non-significant tests would indicate perfect fit of the model to the data. Chi-square statistics of two models were also used in chi-square difference tests, where significant results would indicate better-fitting models and non-significant results would indicate equivalent fit (Werner & Schermelleh-Engel, 2010). Fourth, after identifying the best-fitting models I evaluated the strength and significance of longitudinal path coefficients to interpret variable relationships in the models.

I first tested nested models with strain, self-undermining, and demands as latent variables and current GPA as an observed variable. The initial M1 stable model fit the data well ($\chi^2(777) = 1045.09, p = .000$; RMSEA = .03; CFI = .96; TLI = .96; SRMR = .06; see Table 5) and indicated construct stability over time for strain ($\beta_{T1-T2} = .76, p < .001$; $\beta_{T2-T3} = .83, p < .001$), self-undermining behaviors ($\beta_{T1-T2} = .78, p < .001$; $\beta_{T2-T3} = .82, p < .001$), demands ($\beta_{T1-T2} = .80, p < .001$; $\beta_{T2-T3} = .83, p < .001$), and performance ($\beta_{T1-T2} = .88, p < .001$; $\beta_{T2-T3} = .88, p < .001$). The M2 causal model failed to converge but did not demonstrate negative residual variances or variable correlations greater than 1; to identify the model, I therefore increased the number of iterations and added a starting value to the model to specify the residual variance of T2 and T3 GPA (Muthén & Muthén, 1998–2017). The model again failed to converge. I next added a starting value to specify the variance of the T1 latent strain variable, and the model converged and yielded acceptable fit ($\chi^2(768) = 1035.65, p = .000$; RMSEA = .03; CFI = .96; TLI = .96; SRMR = .06; Table 5). The M3 reversed causal model also converged with these starting value specifications ($\chi^2(768) = 1034.43, p = .000$; RMSEA = .03; CFI = .96; TLI = .96; SRMR = .06; Table 5), as did the M4 reciprocal model ($\chi^2(759) = 1019.69, p = .000$; RMSEA = .03; CFI = .96; TLI = .96; SRMR = .06; Table 5). Although the reciprocal model fit the data best, chi-square difference tests indicated that the added paths did not significantly

improve the model ($\Delta\chi^2(18) = 25.42, p = .114$; Table 5). Additionally, only self-undermining behaviors at T2 and T3 were significantly predicted by any reciprocal paths in the model (see Table 6 and Figure 12).

Alternative model tests. To further test the self-undermining proposition, I conducted tests of several alternative models. I first retested the self-undermining proposition to assess issues with model specifications and/or justifications (i.e., the accuracy of the theory for and implementation of the model specifications; see Kline, 2012), such as with grade (rather than GPA) as the observed performance variable, with latent performance variables rather than observed variables (Muthén & Muthén, 1998–2017), and with additional starting values specified in the model syntax. Moreover, I also tested models that reincluded participants who were initially removed due to response invariance, unreasonable response times, and/or negative person-total correlations per Curran's (2016) recommendation to run and report analyses both with and without the reduced sample from data screening. These alterations did not improve the model, yield more significant model paths, or suggest issues with model specifications and/or justifications. Rather, the alternative models typically required additional starting value specifications to converge and yielded less significant paths and worse model fit.

Second, I retested the model to assess issues of both multivariate outliers and of the synchronicity and timeframes of the model effects (e.g., due to the incongruent time lags between the Western and Southern samples in Table 3). In both cases the M1 models converged, but the M2-M4 models only converged with specified starting values for T2 and T3 GPA residual variances and T1 strain variance. I first assessed for confounding multivariate outlier effects via a series of models with nine cases removed (i.e., the cases had a conservative level of Mahalanobis D significance at $p < .001$; see Kline, 2011). The M4 model fit statistics were not

an improvement over the baseline M1 model ($\Delta\chi^2(18) = 25.26, p = .118$) and were comparable to the original model tests ($\chi^2(759) = 997.14, p = .000$; RMSEA = .03; CFI = .97; TLI = .96; SRMR = .05; see Table 5 for M4 fit in initial tests). Compared to paths in the original model tests (see Table 6), only two demands-SUB paths remained significant ($\beta_{T1-T3} = -.41, p = .002$; $\beta_{T2-T3} = .32, p = .009$), whereas the T1 to T2 demands-SUB path ($\beta_{T1-T2} = .15, p = .055$) and the strain-SUB paths ($\beta_{T1-T2} = -.16, p = .071$; $\beta_{T1-T3} = .24, p = .064$) were no longer significant. I next assessed for confounding synchronicity effects in nested models with the Southern sample removed from the dataset, and the model once again behaved similarly. The reciprocal paths did not improve the M4 model ($\chi^2(759) = 1019.78, p = .000$; RMSEA = .03; CFI = .96; TLI = .96; SRMR = .05) over the baseline M1 model ($\Delta\chi^2(18) = 26.63, p = .086$). Compared to the original model (see Table 6), in M4 the reciprocal paths remained significant in all lagged demands-SUB effects ($\beta_{T1-T2} = .19, p = .022$; $\beta_{T1-T3} = -.40, p = .003$; $\beta_{T2-T3} = .31, p = .012$) and one strain-SUB effect ($\beta_{T1-T2} = -.19, p = .039$), but the strain-SUB path from T1 to T3 was no longer significant ($\beta_{T1-T3} = .23, p = .087$). No other M4 reciprocal paths were significant.

Finally, due to the issues of both model non-convergence and the performance variables' small and non-significant correlations with strain, I tested a series of nested models with only the strain, self-undermining, and demands variables and their respective paths. The purpose of this approach was to assess the three primary paths that constitute the loss spiral. The M1-M4 model paths were therefore identical to those of the initial hypothesis tests except with all paths to performance removed. The M1 stable model fit the data well ($\chi^2(668) = 890.34, p = .000$; RMSEA = .03; CFI = .97; TLI = .96; SRMR = .06; see Table 5) and again indicated construct stability for strain, demands, and performance at β -values nearly identical to the original model tests. Different than the original model tests, the M2-M4 models converged without specified

residual variance and/or variance starting values. See Table 5 for model fit and chi-square difference test statistics. Similar to tests of the full proposition, the reciprocal M4 model fit the data best but did not significantly improve over the M1 model ($\Delta\chi^2(18) = 26.28, p = .094$). Additionally, self-undermining behaviors at T2 and T3 were significantly predicted by reciprocal paths in the model (see Table 6 and Figure 13). Finally, demands at T2 were significantly predicted by self-undermining at T1, which was not a significant path in the full proposition model.

MANOVA. Although the cross-lagged analyses results did not support the self-undermining proposition or study hypotheses, I next conducted a RM MANOVA analysis in SPSS to fully assess the self-undermining proposition per the two criteria for loss spirals. Specifically, significant cross-lagged paths only indicated that the relative order of participants on each variable was strongly related across time points, but not that the study variables augment one another and increase over time (Salanova, Llorens, & Schaufeli, 2010). I therefore conducted the RM MANOVA to assess for differences in demands, strain, self-undermining behaviors, and performance (the dependent variables) between time points T1-T3 (the categorical independent variable). In other words, the RM MANOVA results tested for a within-subjects effect of time on the mean values of self-undermining proposition variables. The results did not indicate a significant multivariate effect, Wilks' Lambda = .965, $F(8, 786) = 1.77, p = .079$, multivariate $\eta^2 = .018$. See Figure 14 for plots of the estimated marginal means. With performance removed from the model, the results also did not indicate a significant effect, Wilks' Lambda = .975, $F(6, 808) = 1.69, p = .121$, multivariate $\eta^2 = .012$.

Discussion

The overall aim of this study was to assess the self-undermining proposition through two methods: computational modeling and statistical analyses of data collected in a longitudinal research design. This dual-method approach had three key purposes. First, computational modeling enabled a formal test of the self-undermining proposition by logically and mathematically specifying the self-undermining proposition in a simulation to better explain and interpret the dynamic relationships involved in JD-R theory. Second, the longitudinal design enabled an empirical test of the self-undermining proposition, as it is a relatively novel and uninvestigated addition to the conceptual model in JD-R theory. Finally, the approach of using both methods enabled a comparison of the integrative results. I next discuss the longitudinal analyses results, prior to comparing the computational and longitudinal findings and describing the limitations and implications of this study.

Longitudinal Results

In the longitudinal study I collected data from a sample of undergraduate students at two universities in the U.S. With this data I tested four study hypotheses (H1-H4) that aligned with the self-undermining proposition of JD-R theory; specifically, that self-undermining behaviors would influence future demands (H3) and demands would influence strain (H1), which would further influence self-undermining behaviors (H2) and performance (H4) to perpetuate the loss spiral of the self-undermining proposition. I tested these hypotheses via two statistical techniques: cross-lagged panel analyses and a repeated measures MANOVA. Together the two techniques enabled a full test of the self-undermining proposition, as the cross-lagged analyses results informed if the participants' relative order on constructs remained the same over time and

the RM MANOVA informed if time exhibited a within-subjects effect on mean scores of the variables over three time points.

Table 4 shows the means, standard deviations, and intercorrelations for all study variables. As seen in the table, bivariate correlations provide initial support for most study hypotheses. Specifically, in initial support of H1, demands positively related to strain at each time point ($.42 < r < .54$); these correlations represent large effects per current meta-analytically derived correlational effect size benchmarks (Bosco, Aguinis, Singh, Field, & Pierce, 2015). Furthermore, strain positively related to self-undermining behaviors at all time points ($.25 < r < .38$; large effects) in support of H2, and self-undermining behaviors positively related to demands at all time points ($.19 < r < .33$; medium and large effects) in support of H3. However, the results did not support H4, as strain did not significantly relate to performance and the correlations were both positive and negative ($-.05 < r < .05$). Interestingly, performance outcomes only significantly related to self-undermining behaviors ($-.16 < r < -.34$; medium and large effects), which was not hypothesized per JD-R theoretical principles. Overall, bivariate correlations suggested that the core variables of the loss spiral (i.e., demands, strain, and self-undermining behaviors) positively influenced one another as hypothesized, but that strain did not negatively influence performance. Moreover, the mean scores of demands and performance (i.e., T1-T3 GPA in Table 4) increased at each time point of the study. Nonetheless, mean values of strain were identical at each time point and mean values of self-undermining behaviors dropped at T2 and then increased at T3 to slightly higher than the T1 mean value. Altogether, the initial results supported H1-H3, did not support H4, and suggested that mean scores increased over time for two of the four variables in the self-undermining proposition. In other words, the results indicated that variables in the self-undermining proposition feedback

loop did influence one another, but with no effect on performance outcomes and without a full loss spiral of increased mean scores over time.

Hypothesis tests. Contrary to the initial correlational evidence, the cross-lagged results did not support the premise of the self-undermining proposition. More specifically, the initial model results suggested that the addition of reciprocal paths did not significantly improve model fit compared to the baseline model. Results indicated partial support for Hypothesis 2 (H2), as strain did influence future self-undermining behaviors, but (a) the effect was only significant from T1 strain to self-undermining at T2 and T3, and (b) the coefficients switched from positive (T1-T2) to negative (T1-T3) in significant model paths. The results did not support hypotheses that demands influence strain (H1), self-undermining behaviors influence demands (H3), and that strain influences performance (H4).

Alternative cross-lagged model tests did not provide further support for the study hypotheses or the premise of the loss spiral. In these tests I assessed for confounding effects from model specifications, multivariate outliers, the exclusion of participants originally removed for careless or inattentive responding, incongruent time lags, and nonlinear relationships between performance and other model variables. In the former four alternative test results there were often less significant reciprocal paths in the model (but never additional significant paths) and their addition never improved model fit over the baseline model. In the latter test of models without performance, a new significant path was found, but the addition of reciprocal paths once again did not improve model fit.

In the RM MANOVA analyses, the non-significant Wilks' Lambda and small partial eta-squared (i.e., an indicator of effect size) did not indicate a multivariate effect of time on participants' mean scores of demands, strain, self-undermining behaviors, and performance. If

significant results were found, subsequent repeated measures ANOVAs could have further informed interpretations of the significant differences on the study DVs. Nonetheless, RM MANOVA plots showed increasing estimated means over time for demands, strain, and self-undermining behaviors (see Figure 14). Additionally, the estimated means of performance dropped from T1 to T2 before rising again at T3 (see Figure 14). The estimated mean changes between time points were no greater than .08 for all variables. Altogether, the results show that there were increases in means of the self-undermining proposition variables over time, but the overall effect of time was small and non-significant.

In summary, the longitudinal results did not comprehensively support or identify the self-undermining proposition. Although descriptive statistics and correlations provided initial evidence for the covariances and main effects stipulated in JD-R theory, the hypothesis tests did not. In all cross-lagged models tested in this study, the addition of causal, reversed causal, and/or reciprocal model paths failed to significantly improve model fit over the stability model. Additionally, most added model paths were non-significant and failed to support the general main effects in the self-undermining proposition. Significant model paths were also antithetical, in that both demands and strain at T1 influenced self-undermining behaviors at T2, but the coefficient of both effects switched signs when predicting self-undermining behaviors at T3. These results imply that the loss spiral is invalid and that the variables in the self-undermining proposition do not augment one another over time, but rather may fluctuate in ways that were not empirically studied and were not directly assessable in the computational model specifications in this study. Furthermore, although analyses of plots generated in the RM MANOVA did suggest an upward trend in the mean values over time, the RM MANOVA results were non-significant (and thus not supportive of the study hypotheses) and had small effect sizes. The mean increases

over time therefore cannot be interpreted to represent changes that either paralleled those in the computational model or meaningfully and comprehensively explained variance in study variables.

Comparison of Longitudinal and Computational Results

The separate and integrative computational and longitudinal results were not supportive of the self-undermining proposition; therefore, it's appropriate to question the viability of the proposition as the results do not support JD-R theory as a whole. Separately, the computational and longitudinal methods failed to either plausibly simulate or statistically identify the paths and relationships in the self-undermining proposition. When compared, the two sets of results were contradictory, incongruent, and further unsupportive of the self-undermining proposition. Beyond implying that the self-undermining proposition is unviable, the discrepant results reflect limitations and differences of these two methodologies. Moreover, these methodological limitations and differences reflect broader limitations and inadequacies of JD-R theory. I next compare and interpret the integrative results, discuss the methodological limitations and implications of this study, and finally describe the limitations of JD-R theory that were identified and/or deduced in this study.

Given the issues encountered in both the model and in the statistical analyses, I primarily relied on qualitative comparisons to interpret the integrative results of both study methods (Busemeyer & Diederich, 2010; Vancouver & Weinhardt, 2012). Individually, the two sets of results did not support the self-undermining proposition. First, the computational model results provided a rudimentary example of variable trajectories in a simulated loss spiral per the self-undermining proposition, in which values of demands, perceptions, strain, and self-undermining behaviors all rose at increasing rates while performance fell at an increasing

rate (see Figures 5 and 6). Although these simulations of anticipated effects generally suggested initial support for the self-undermining proposition, the model functions were fundamentally reliant on the JD-R theoretical premises and consequentially yielded a perpetual loss spiral (via a positive feedback loop) of decreased performance and increased demands, strain, and self-undermining behaviors. Second, and conversely, the longitudinal results did not provide evidence for the main effects and loss spirals in the self-undermining proposition. Despite initial descriptive and correlational evidence for the self-undermining proposition, the cross-lagged and RM MANOVA results rejected the study hypotheses.

The results of both studies when viewed together failed to support the study hypotheses or provide additional evidence consistent with the self-undermining proposition. Given the limitations of the computational model (that I further discuss in the limitations sections), I primarily compared the longitudinal results to output from simulations with the final model specifications and without additional exogenous variable effects (see Figure 6). The output generally showed variable trajectories in an individual-level loss spiral if the self-undermining proposition were valid per JD-R theory. I therefore compared the simulation output to the cross-lagged and RM MANOVA results to further interpret these effects and the study hypotheses. Although the RM MANOVA plots in Figure 14 provided insight into the variable trajectories in the longitudinal data, the plots are notably based on small and non-significant RM MANOVA effects.

Overall, the empirical results did not mirror the simulation effects of any study hypothesis. First, H1 predicted a positive influence of demands on future strain. In the computational model output in Figure 6, this relationship is conveyed by increased demands over time that correspond with increased strain at an increasing rate of change. Statistically, the

correlations indicated that these variables were positively associated with large effect sizes. Nonetheless, there were no significant cross-lagged effects of demands on later strain and all non-significant effects were negligible ($\beta < .08$). The RM MANOVA plots also did not show these lagged effects; for example, one might interpret this effect if demands had risen from T1 to T2 and strain correspondingly rose from T2 to T3. Figure 14 shows the inverse, as demands rose from T2 to T3 whereas strain rose from T1 to T2. Thus, the longitudinal results do not show definitively a lagged effect like the computational model output and H1 was not supported. However, the results also do not negate definitively the presence of these effects at other time points or intervals. For example, additional timepoints earlier in the academic semester could inform if the T1-T2 changes in strain related to prior changes in demands. The effects may also appear at other time points or intervals as demands fluctuate throughout the academic semester.

H2 predicted a positive influence of strain on future self-undermining behaviors. The computational model simulated this relationship via increased self-undermining behaviors at an increasing rate of change that corresponded to prior rises in strain. The longitudinal data showed significant relationships between the two variables, such as initial large positive correlations. However, the cross-lagged results did not support the relationships as hypothesized or simulated per JD-R tenets. Rather, although there were significant paths from T1 strain to self-undermining behaviors at T2 and T3, the coefficients fluctuated from negative (i.e., β_{T1-T2}) to positive (β_{T1-T3}). Furthermore, the path from T2 strain to T3 self-undermining behaviors was negative and non-significant, and there was no significant overall cross-lagged relationship given the comparatively small and non-significant paths from self-undermining behaviors to strain. Overall, these empirical results were ambiguous and suggested that individuals' relative standings on the strain and self-undermining behaviors constructs were not comparatively stable

over time. Rather, although strain did predict future self-undermining behaviors, the effect varied between positive and negative depending on if the outcomes were temporally proximal or distant within the parameters of this study. The results did not show a loss spiral like the computational model output, and only suggested that strain predicted self-undermining behaviors in ways that were unclearly related to time and varied between individuals. Thus, H2 was not supported in the integrative results.

H3 stated that self-undermining behaviors positively influence future demands. The computational model output showed this general relationship via increased demands perceptions as self-undermining behaviors rose. This relationship was statistically supported by medium and large correlation coefficients, but there were no significant cross-lagged effects. Rather, the results showed the inverse of the hypothesized relationship; self-undermining behaviors were predicted by demands but the relationship was not reciprocal. Specifically, T2 demands were positively influenced by T1 self-undermining behaviors, whereas T3 demands were not influenced by T1 self-undermining behaviors ($\beta = .001$) and minimally negatively influenced by T2 self-undermining behaviors; all relationships were non-significant. Conversely, self-undermining behaviors at T2 and T3 were significantly predicted by demands at T1 and T2. Similar to issues in interpreting H2, however, the cross-lagged effects between self-undermining behaviors and demands ambiguously varied as either positive or negative. The computational model output did not show these varying relationships and the RM MANVOA plots generally showed that the variables both rose over time. Thus, H3 was not supported, and the results suggested that demands were not predicted by prior self-undermining behaviors but instead that self-undermining behaviors were influenced by prior demands and that the effects may differ depending on time and/or other confounding variables.

Finally, in H4 I predicted that strain would negatively influence future performance. In the computational model output, this was demonstrated by decreased performance over time at an increasing but proportionally smaller rate of change than the rising strain values. Nonetheless, this hypothesized main effect was not supported by the empirical results. In contrast to supportive correlational evidence for the first three hypotheses, H4 was not supported and all correlations between strain and performance variables were small, non-significant, and ambiguously varied between time points as either positive or negative. The empirical results also showed no significant cross-lagged effects of strain on performance. Thus, these results indicated that participants' relative standings on the strain and performance constructs ambiguously and unrelatedly varied over time points. Interestingly, the RM MANOVA plots in Figure 14 showed that mean performance values initially decreased as strain means rose, prior to strain stabilizing and performance rising to prior levels. These integrative findings reject H4 as the longitudinal data did not show the anticipated effects from the computational model simulations. Although the Figure 14 plots seemingly convey some relationship between strain and performance, the results did not show correlations, cross-lagged effects, or augmentation of mean values over time.

In summary, comparing the integrative results further failed to support the hypothesized effects and loss spirals of the self-undermining proposition. The results were contradictory, and these incongruencies relate to differences in the methodologies through which they were obtained. First, the computational model simulations showed the expected effects in a hypothetical loss spiral but revealed theoretical problems determining when, how, or in what context the spiral may change or falter. These issues relate to the system dynamics modeling approach of specifying and simulating intraindividual change; in this study, this manifested in

simulations of loss spirals within individual subjects. However, I could not simulate variability between subjects beyond altering values of variables in sensitivity analyses and/or including or excluding variables from the model. In other words, the specified model functions were assumed to represent these variable relationships in all individuals, and I could not assess or simulate differences in these function specifications between individuals. Second, the empirical study methods were similarly limited, in that I tested the self-undermining proposition in the aggregate but did not assess variability between individuals. When comparing results from the two methods, the correlations supported most bivariate relationships or direct effects in the self-undermining proposition, but the cross-lagged and RM MANOVA results neither showed these effects nor supported the study hypotheses. Thus, the overall implication of these interpretations is that there may be between-subjects effects or variance that I could not capture or assess with the methods of this study. Researchers should consider alternative methods that enable more robust quantitative comparisons of computational and empirical results. Additionally, researchers should choose methods that enable assessments of the intraindividual change that is conceptualized and modeled in JD-R theory, as many common methods (such as those in this study) use aggregate-level statistical analyses to interpret and infer individual-level effects.

Although there are certainly methodological limitations to consider in these interpretations, the results nonetheless also suggest that current JD-R theory has several limitations and issues. Moreover, although there are limitations and issues of the self-undermining proposition, the overall JD-R theoretical model also has several limitations that relate to the findings in this study. I next describe these methodological and theoretical limitations and implications for future research.

Methodological Limitations and Implications

Statistical power. First, the overall null findings and unimproved cross-lagged model fit in the empirical study may reflect issues of statistical power. Although power analyses initially guided the aspired sample size in this study (i.e., via Monte Carlo simulations in Mplus to estimate the sample size necessary to minimize bias in parameter estimation), the final dataset was substantially reduced after removing inattentive responders, multivariate outliers, and responses with person-level missingness. All decisions to remove participants were guided by recommended best practices in research literature, but Curran (2016) noted that techniques for removing any participants from datasets assume some Type I error. In other words, in using these techniques “there is potential for the good to be thrown out with the bad” (Curran, 2016, p. 14) if or when false positives occur and valid responses are flagged as inattentive responders. Nonetheless, as Curran emphasized, the opposite is not ideal either; Type II error rates are maximized when researchers refrain from any data screening of careless, inattentive, and/or outlier responses. In this study, I aimed to err towards Type II error and removed participants only when data screening procedures suggested careless and/or inattentive responses via multiple issues in the data (e.g., short response time and long-string responding) or overarching single issues (e.g., negative person-total correlations). Although I further tested many alternative models with the removed participants’ data reincluded in the analyses, the results were similar or worse in all cases. Therefore, although the results did not clearly suggest that my data screening choices were the primary influencer of null and/or contradictory findings in this study, the process of reducing the sample may have unintentionally removed valid responses from the dataset and/or failed to remove invalid responses.

Additionally, a predominant lack of statistical power (i.e., due to the overall sample size regardless of careless/inattentive responders) may have ultimately biased the statistical results and inhibited comparisons to the computational model results. It may be the case that a larger sample size in this study would yield statistical results that support or parallel the results of simulations. Further research with larger sample sizes may enable a more robust test of the self-undermining proposition for comparison to computational model simulations. In such investigations, researchers should aim to optimize study design by carefully calculating power estimates in consideration of potential sample size reductions during data screening. Although power analyses are not well defined in path model literature (Arnett, Pennington, Willcutt, Dmitrieva, Byrne, Samuelsson, & Olson, 2012), and are not often reported in studies with cross-lagged analytical methods, there are resources available in the literature to inform these research design decisions (see Arnett et al., 2012; Kline, 2011; MacCallum, Browne, & Sugawara, 1996).

Measurement. Second, the measures used in the empirical study also may have presented several limitations that influenced the incongruent study results. For example, the self-undermining behaviors scale in this study had three noteworthy limitations. First, it was a newly-developed measure based on the original scale from Bakker and Wong (2016). More research is necessary to further support the validity and reliability of the measure in academic contexts. Second, the poor fit of the single-factor model may indicate that there are sub-dimensions of academic self-undermining behaviors in need of further theoretical and empirical investigation. This also relates to a third limitation; that further research should clarify the construct of self-undermining behaviors to incorporate and acknowledge the intentional or unintentional nature of these behaviors. Although I considered this distinction in computational model

development, the self-reported longitudinal measure relied on an assumption that individuals were aware of their self-undermining behaviors but that this awareness did not influence the effect of behaviors on demands. Thus, meaningful variance may be unaccounted for in this study if individuals did behave self-underminingly but did not report it due to a lack of awareness.

Additionally, the performance measures in this study related to self-undermining behaviors but not to demands, strain, or performance. The use of self-reported grades may have biased participants' scores on these variables, as their validity relied on an assumption that students would provide accurate responses. I attempted to mitigate these issues by providing instructions for students to look up their grades online, but future research would nonetheless benefit from the use of objective performance measures (e.g., GPA or course grade data obtained from the academic institutions) either instead of or in conjunction with self-reports. If these methodological changes still yielded null relationships or effects of strain on performance, this might suggest that behaviors are a more profound outcome of academic demands and antecedent to academic performance. The empirical results of this study suggest that this premise needs further investigation, as self-undermining behaviors were the only significant predictor and/or correlate of performance. Further empirical and computational investigations of these relationships may inform whether these results are simply a unique result of this study or represent students' experiences in general.

Another similar measurement limitation was the operationalization of constructs in this study in consideration of alternative conceptualizations that researchers may consider. For example, in this study I operationalized and measured strain as exhaustion. However, there are numerous alternative strain outcomes that individuals may consider in future research. Other studies in JD-R and OHP literature have assessed outcomes such as attitudes (e.g., turnover

intentions or organizational commitment; Bakker, Demerouti, & Schaufeli, 2003), behaviors (e.g., health behaviors, absenteeism and presenteeism, counterproductive workplace behaviors, or workplace mistreatment; Balducci, Schaufeli, & Fraccaroli, 2011), psychological distress (e.g., anxiety or depression; Shimazu, Bakker, Demerouti, & Peeters, 2010) and other health impairments (e.g., health complaints, workplace accidents, or illness and disease; Johnson & Hall, 1988; Nahrgang, Morgeson, & Hofmann, 2011). Researchers should consider alternative constructs in future studies on the self-undermining proposition and/or JD-R theory, as different strain operationalizations will have different implications for appropriate hypotheses and computational specifications. Moreover, different operationalizations may provide opportunities to further test and probe the current propositions in JD-R theory. For example, operationalizing strain as behavioral health outcomes (e.g., health behaviors, substance use, absenteeism and/or presenteeism, etc.) presents an interesting research question regarding the distinctions between strain-related behaviors and self-undermining behaviors.

Other measurement limitations included the modification of study measures for academic contexts rather than job contexts, as well as dropping one or more items from all measures due to insufficient fit statistics and loadings in factor analyses and initial issues with reductions in scale reliability over time points. Although the final reliability and correlation coefficients suggested that the modified scales operated as intended, measurement error may have contributed to the many null findings and insignificant paths in the reciprocal models. Therefore, future research should incorporate further reviews of measures in other disciplines and their utility in JD-R and/or OHP research among students. For example, the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, Smith, Garcia, & McKeachie, 1991; 1993) is a measure in education and psychology literature to assess students' motivation and use of learning strategies.

Several constructs in the questionnaire may apply or relate to those in JD-R and OHP literature, such as the MSLQ factors of intrinsic and extrinsic goal orientation, control beliefs about learning, and self-efficacy for learning and performance, among others.

Regardless of the measures used, researchers should also consider the response options of scales that are modified for academic contexts. For example, I adopted and modified the QWI measure of academic demands after identifying no favorable alternatives in an extensive literature review. However, I retained the response options from the original QWI that range from “Less than once per month or never” to “Several times per day” (see Appendix C). Although the scale demonstrated acceptable reliability and a normal distribution, the measurement of strain may improve with alternative response options that better capture the time bounds of the study. Furthermore, these improvements would likely also improve comparisons to similar computational model simulations.

In addition to addressing the psychometric limitations of this study, researchers comparing empirical and computational results should also consider first developing and testing computational models and then designing and assessing longitudinal results that incorporate the additional variables and relationships considered in computational model development. For example, in the computational model of this study I included constructs of appraisal, desires, cognitive ability, and behavioral intention. Future research that measures and incorporates these variables in empirical tests of the self-undermining proposition may yield more direct comparisons to results of computational simulations and the changes in variable trajectory after accounting for other individual difference factors. Importantly, these decisions should not be made in isolation, but rather in consideration of other aspects of the study design and its limitations. For example, deciding to incorporate additional study variables would also carry

implications about the statistical power, structural models, and statistical analyses in empirical research, all of which also influence the ability to compare empirical and computational results.

Time intervals. Third, researchers should aim to optimally align measurement with the temporal parameters of the study. In both methods of this study the time lags were specified to capture fluctuations in students' demands during the latter weeks of the academic semester and consequential effects on strain, behavior, and performance outcomes. Nonetheless, two longitudinal study limitations in these time lags are worth noting.

First, the time lags were inconsistent between samples, and the Southern sample T2-T3 time lag was substantially shorter than other lags in the study. Additionally, the T3 Southern survey was available for a shorter period of time. Although I assessed for confounding effects of incongruent time lags in the cross-lagged analyses, these may have biased the study results in ways that were not captured in the empirical analyses.

Second, the multivariate results suggested that the time lags were not sufficient to capture fluctuations in JD-R variables, as there was no significant effect of time on dependent study variables and several significant path coefficients changed their sign over time (i.e., from positive to negative or vice versa). These changes could reflect general issues with the data quality or suggest that there were more frequent temporal fluctuations that were not captured in this study. Related to calls for future research assessing microprocesses in the JD-R model (Bakker & Demerouti, 2017), future research of feedback loops and/or spirals in student populations may benefit from alternative time bounds that capture more rapid fluctuations in academic demands over the semester. If different time bounds are chosen, researchers should also incorporate these time bounds if or when developing computational models to compare to empirical results.

Chosen methods. Finally, the chosen study methods may have broadly limited comparisons of the integrative study results. Researchers may consider alternative longitudinal and/or computational methods in future tests of the self-undermining proposition. Beginning with the former, cross-lagged analysis was chosen in this study to directly replicate the methods of JD-R gain spiral studies to test loss spirals in the self-undermining proposition. Moreover, this decision was informed by research suggesting that cross-lagged analytical techniques can be useful when chosen in conjunction with theoretical purposes, such as the general goals of this study to test the theoretical premises in the self-undermining proposition (see Selig & Little, 2012). Nonetheless, cross-lagged analysis has been criticized in research literature (see Hamaker, Kuiper, & Grasman, 2015; Kenny, 1975; Locascio, 1982; Rogosa, 1980) and researchers may consider other analytical approaches to assessing loss spirals and other JD-R or OHP theoretical propositions. For example, latent growth curve modeling (LGCM) may be especially applicable to studies of gain and loss spirals in JD-R theory; advantages over cross-lagged panel analysis and/or RM MANOVA include that LGCM enables assessments of many patterns of change, change with uneven time metrics, discontinuous change, and can be used for multi-group analysis of separate growth patterns among groups (M. Prince, personal communication, February 27, 2018; see Curran, Obeidat, & Losardo, 2011; Grimm, Steele, Ram, & Nesselrode, 2013; Preacher, 2010). Graphs of the identified trajectories in LGCM could also provide an opportunity to better compare the statistical results to those of computational simulations. Additionally, growth mixture modeling (GMM) and/or latent class growth analysis (LCGA; see Bauer & Curran, 2003; Jung & Wickrama, 2008; Nylund, Asparouhov, & Muthén, 2007) are other relevant methods that may enable comparisons to computational models of the self-undermining proposition. Specifically, these methods are similar to LGCM but also assess

for latent classes or profiles of trajectories over time (M. Prince, personal communication, March 20, 2018; Jung & Wickrama, 2008). As modelers and researchers continue to assess for individual difference factors that influence JD-R processes, these methods may enable richer and more robust tests and comparisons of simulations and empirical results.

In addition to this study's statistical limitations, limitations of the computational modeling methods of this study may have influenced the contradictory integrative findings. Computational modeling is a relatively novel approach to theory development in organizational sciences and the results of this study may simply indicate that more work is necessary to develop an adequate computational model of the self-undermining proposition and/or JD-R theory. Nonetheless, several other limitations of the computational model may have played a role in the incongruent findings of this study.

For example, although I developed an initial computational model using tutorials and best practices (e.g., Vancouver & Weinhardt, 2012) and based the model specifications on theoretical premises, the model was limited by its inability to simulate anything but a perpetual positive feedback loop. While changes in the exogenous variables did augment or attenuate relationships in the model, changes within the final model parameters and specifications did not suggest circumstances in which the loss spiral "breaks" or ceases to perpetuate. Furthermore, the results suggested that the detrimental loss spiral outcomes of strain, self-undermining behaviors, and demands would endure (i.e., they would not falter or diminish with time) even if the loss spiral were to end. This is conceptually implausible; if this were the case, I speculate that academic institutions' enrollment numbers would not be at the levels they are today. Moreover, the longitudinal results generally support this notion and suggest that the computational model results are empirically implausible.

Assuming that my conceptualizations and specifications of JD-R theory in the longitudinal and computational studies were valid, these findings may be an artifact of the isolated research design in this study. Specifically, I longitudinally and computationally tested only the self-undermining proposition rather than the overall JD-R model. This approach was warranted to align the simulation with the study goals and longitudinal methods, but nonetheless may have been a critical or underlying reason for these evaluation results. In support of this interpretation, authors have argued that the health impairment and motivational processes should be studied in conjunction rather than in isolation (Bakker & Demerouti, 2017; Schaufeli & Taris, 2014). Future research with designs like this study, but with more complete tests of JD-R theory, may enable better interpretations and comparisons of longitudinal and computational results that account for the many variables and paths in the theory.

Conversely, if my applications of JD-R theory to the computational model were invalid in some manner, these findings may indicate broader theoretical limitations worthy of further investigation. Given that I developed a simple model with basic equations to specify variable relationships – a technique that has been supported and encouraged in prior research – this interpretation is plausible. In such case, the overall results would have several broad implications for future research on JD-R theory. I next describe these potential theoretical limitations and their implications for future research.

Theoretical Limitations and Implications

First, the contradictory study results reflect a broad limitation regarding the application of OHP theory and concepts to a student population in an academic research context. Although I based this design on other studies with a similar approach, this is nonetheless a proportionally less common perspective in OHP literature. Beyond the noted methodological limitations, these

study results also suggest that the premises and propositions of JD-R theory in work-related contexts are fundamentally inappropriate or incongruent with school-related contexts. In other words, neither the computational model nor the empirical study yielded evidence to suggest that JD-R theory was an appropriate paradigm for conceptualizing and evaluating relationships among students' demands, strain outcomes, self-undermining behaviors, and/or performance. Rather, there are many fundamental differences between work and academic contexts that were not captured in this study on the basis of its JD-R theoretical foundation. For example, students often are tasked with balancing demands and performance in multiple courses or “jobs” (each with their own demands, deadlines, performance outcomes, and associated strain and/or other well-being outcomes) in addition to demands and responsibilities in work life (e.g., part- or full-time work in addition to school) and in personal life (e.g., social interests and obligations, family and nonwork life, etc.). Given that students self-selected into this study via the enacted recruitment materials and methods, it is plausible that students with noteworthy high or low demands chose not to participate in this study. Moreover, this sampling bias is an issue that is likely influential in all studies of students and/or academic contexts, especially in JD-R and OHP research where the constructs of interest are variables that may detrimentally influence the external validity and generalizability of the study methods and results. Future research in academic contexts should therefore incorporate these considerations into study design and sampling and recognize the limitations of JD-R theory and other OHP theories, models, and concepts in such populations and research contexts.

Second, the results of this study indicated several theoretical limitations that I primarily derived from computational model evaluations. For example, related to issues of OHP theories in academic contexts, the computational model in this study incorporated several ad hoc

assumptions based on other theory and empirical evidence. Although these assumptions may not have convoluted the study results given that the additional exogenous model variables were specified to yield no effect on the initial study model, a general limitation of this approach is the use of other informal theories to inform formal theory development of the informal JD-R theory. In other words, if or when researchers in various psychology fields further utilize computational modeling to develop and/or test formal theories, they should consider the inherent limitations that come with basing model specifications and/or ad hoc assumptions on other informal theories. Moreover, if the method continues to grow as a technique among psychology researchers, the overall discipline of psychology may benefit from formal tests of the theories and paradigms that are integrated within or between its many fields. For example, in this study I used the TPB to inform ad hoc assumptions and specify the Self-Undermining Behaviors function. The TPB has been used by many psychology researchers to explain or interpret human behavior, and therefore may be a prototypical example of a theory to formally test via computational modeling. Furthermore, JD-R theory propositions have been inspired by many different psychological theories (see Bakker & Demerouti, 2017), and I anticipate that future developments in JD-R theory will be informed in a similar manner. For example, Bakker and Demerouti (2017, p. 277) stated that “where other theories can inform us regarding those processes, we should build on them, because it is in this way that we can create new knowledge.” As researchers continue to build and test JD-R theory, they should especially consider the validity and premises of other theories that influence these decisions.

Beyond the limitations of the applicability and validity of other informal theories, my study results also indicated several potential limitations and implications specific to JD-R theory. First, the results suggest that current JD-R conceptualizations in Propositions 7 and 8 of loss

spirals and/or dual processes are insufficient and are not generalizable to all individuals and contexts. Specifically, in this study I conceptualized strain, self-undermining behaviors, and demands as dynamic variables that are dependent on time. These specifications aligned with the premises of the self-undermining proposition, as well as other premises of JD-R theory (e.g., homeostasis), but nonetheless resulted in a model that essentially augmented itself. Breaking the loss spiral would require additional specifications or step changes to the exogenous qualifier variables of each dynamic variable's function. For example, the loss spiral could falter with simultaneous step changes of substantially decreased appraisal, increased desires, decreased behavioral intentions, and reduced demands responsiveness. I did not measure these variables in the empirical component of this study and cannot directly compare these alternative computational model specifications to these empirical data. In line with recent calls for further investigations of microprocesses (e.g., Bakker & Demerouti, 2017) and dynamic relationships (e.g., Taris & Schaufeli, 2014) in JD-R theory, this may therefore be a viable area for future empirical research that assesses the impact of individual factors (e.g., desires, cognition, personality, habit, etc.) and time on JD-R variables and processes. Nonetheless, altering exogenous variable specifications in this study model would still fail to account for any reductions in the variables' values after that time point (i.e., returning to baseline or homeostasis), as they would instead continuously remain at their respective y-values from the time point when the rate of change fell to zero. Therefore, future research should consider these issues and recognize that effects in gain and/or loss spirals will vary depending on individual differences in values on latent constructs (e.g., high vs. low demands and perceptions), moderating or confounding variables (e.g., appraisal, personality, resiliency, coping, physiological response systems, etc.), the context (e.g., the number and types of performance

outcomes; job or school characteristics such as task variety, feedback, etc.), and/or other individual differences in susceptibility to loss spirals. Furthermore, individual differences in behaviors may be influential in other parts of Propositions 7 and 8 and the overall JD-R model, such as the effect of coping behaviors on the path from demands to strain outcomes.

Second, the prior issues relate to another limitation of JD-R theory; that the theory needs to be respecified to remedy its insufficient consideration of individual differences in JD-R theory development and testing. JD-R is a model or framework of intraindividual processes of job characteristics and well-being but does not adequately account for individual differences in these processes. For example, issues of generalizability of gain and loss spirals exemplify this insufficiency. However, beyond the most recent JD-R propositions, the overall theory may not be generalizable to all individuals and contexts and current JD-R specifications do not clarify or specify ways to consider these limitations in research. For example, personality variables may influence other aspects of the model, such as conscientiousness influencing effects of motivation and strain on performance, emotional stability influencing the path from demands to strain, agreeableness influencing the effect of motivation on job crafting (e.g., in relationship crafting), and other potential confounding personality effects. As another example, awareness or other cognitive constructs could confound relationships in gain spirals and individuals' enacted job crafting behaviors. Although individual differences are considered in Proposition 5 of JD-R theory (i.e., that "personal resources such as optimism and self-efficacy can play a similar role as job resources;" Bakker & Demerouti, 2017, p. 275), the overall JD-R model does not account for other effects of individual differences. Thus, researchers should better consider and emphasize individual differences in the JD-R theoretical model, as well as in research and practice using the JD-R as a theoretical foundation. Beyond conceptual considerations in study design (e.g., when

considering variables and constructs of interest), researchers should also consider individual differences when determining data collection and analytical methods. Specifically, the JD-R is a model or framework of within-subjects processes but is often statistically assessed at the aggregate level. This issue was exemplified by the methodological limitations of the statistical methods in this study and why other methods (e.g., LGCM) are more appropriate to test JD-R theory and how its applicability and generalizability varies between individuals.

Third, another noteworthy theoretical limitation identified in this study is the inattention to the role of time in JD-R processes. Similar to the prior noted limitation, the JD-R is a model or framework of processes over time but neglects the differential and varying effect of time on variables and paths in the model. The methodological limitations of this study also exemplify this issue and reflect that this is a clear limitation of the overall JD-R theory. For example, the contradictory integrative results and null longitudinal results may be due to inappropriate time intervals, and self-undermining proposition effects may be identifiable at shorter time intervals in academic contexts (e.g., hourly or daily intervals to assess individuals' demands, strain, and self-undermining behaviors). However, if one were to replicate this study, current JD-R theory does not adequately inform what those time intervals should be. Moreover, JD-R theory does not inform what time intervals should be considered as appropriate in other studies of JD-R processes, and researchers have noted the uncertainties of these processes at varying time intervals (e.g., Bakker & Demerouti, 2017). A relevant other consideration is homeostasis; JD-R theory was developed from other theories that incorporate homeostasis, but current JD-R theory does not incorporate these tenets. For example, in this study the null longitudinal results may reflect that individuals experienced short-term loss spirals of increased demands, strain, and self-undermining behaviors (e.g., hour- or day-level effects as individuals strive to complete

coursework prior to upcoming and temporally proximal deadlines) but that individuals' physiological and psychological systems returned to homeostatic levels after demands dissipated (e.g., after turning the assignment and recovering). Although further research would be necessary to test these suppositions, these results do support an overall sentiment that JD-R theory should be respecified to clarify how the presence, strength, and/or direction of effects vary at different time intervals.

Finally, the study results reflect that current JD-R theory is limited by insufficient and inappropriate conceptualizations of dual motivation and health impairment processes. Specifically, current JD-R theory inadequately explains dual processes both in isolation (e.g., the isolated test of the health impairment process in this study) and when integrated (e.g., in the overall model of both processes). When specifying the computational model strain function, two specific issues exemplified this overall limitation of JD-R theory; that is, I encountered specification issues due to inconsistent conceptualizations of buffering/moderating effects in JD-R theory, as well as inconsistent theoretical conceptualizations of strain and motivation as separate aspects of well-being.

Regarding the former dual-process issue in this study, I specified the Strain function to incorporate the buffer or moderation effect of resources on the relationship between demands and strain. This specification reflected Proposition 3 of JD-R theory, but JD-R theory did not inform if resources should attenuate or invert the effect of demands on strain. Although I conceptualized the buffer effect as a reduction in the rate of change for strain, this may be unfounded; in some cases resources may invert the rates of change in strain over time such that strain peaks and decreases at a certain level of resources. To test this notion, I applied a step

change to the model simulation where resources inverted from 1 to -1 at Week 2.³ As suspected, this led to all model variables shifting their rate of change from a positive to a negative value (and vice versa for performance). Thus, JD-R theory researchers should further investigate and clarify the circumstances that influence varying buffer effects of resources. These clarifications could then enable more accurate or precise hypotheses and specifications in subsequent empirical research and computational modeling.

The latter dual-process issue was arguably more impactful in this study and relates to the use of the If-Then conditional statement in the Strain function equation. As described in the Model Building section, this specification was chosen to represent the health-impairment process of the superordinate dual process model in JD-R theory; that strain outcomes should only result when perceived demands exceed the individual's desired demands. In other circumstances, such as equivalent perceptions and desires or cases where desires exceeded perception, the Strain output would be zero. However, this conditional specification ultimately reinforced the perpetual positive feedback loop and lack of negative feedback loops (i.e., lack of trajectory inversion from positive to negative or vice versa) in model simulations. In other words, although the dynamic variable specifications augmented the simulated spiral and increased rates of change over time, the conditional Strain specification specifically prevented variable trajectories from cresting and changing their direction. For example, in instances where Strain output equaled zero (e.g., specifying a step change to raise desires higher than perceptions at Week 1) the Strain trajectory leveled off but never decreased (i.e., the Strain line's slope became zero and the y-value of Strain remained stagnant through Week 5). Although Strain therefore would cease to increase over the

³ The change from 1 to -1 is counterintuitive, in that it is meant to signify an increase in resources. An alternative, more intuitive approach could be to respecify the initial resources value as -1 and add a negative (-) value to the resources variable in Equation 11. Then, $-1 < \text{resources} < 0$ would indicate insufficient resources to alter the loss spiral, and $0 < \text{resources} < 1$ would indicate sufficient resources to do so.

duration of the model simulation, the dynamic Self-Undermining Behaviors, Demands, and perceptions variables continued to increase. If the model were to continue past Week 5, the value of perceptions would eventually surpass desires and the Strain function would resume a positive, non-zero rate of change. In other words, halting the rate of change for Strain faltered the loss spiral within this model's time bounds, but the loss spiral would eventually resume at later time steps in an infinite simulation. JD-R theory needs to be respecified to clarify and inform if or when strain should decrease when desired demands exceed perceived demands.

Overall, both prior issues and their influence on this study support the postulate that it is inappropriate to conceptualize strain and motivation as separate aspects of individual well-being in the dual JD-R processes. Although this distinction is not always clearly specified in the literature, this conceptualization appears implicitly common in JD-R research (see Bakker & Demerouti, 2007; 2017) and some authors have even explicitly categorized well-being as the outcome of resources (i.e., in the motivation process) and strain as the outcome of demands (i.e., in the strain process; see Schaufeli & Taris, 2014), suggesting that strain is *only* the negative outcomes of demands and is conceptually distinct from well-being. These inconsistent conceptualizations may reflect different semantic perspectives, but the results of this study instead point towards the larger concern that “the JD-R model suggests that the health impairment and motivational processes are independent, but it is quite possible that they represent two sides of the same coin” (Schaufeli & Taris, 2014, p. 57). Figure 1 depicts this concern, in that both the health impairment process and motivation process involve job characteristics (i.e., demands and resources, respectively) influencing individual outcomes (strain and motivation) that predict performance. Furthermore, recent JD-R propositions suggest that individuals' outcomes (strain and motivation) influence or predict their behavior (self-

undermining or job crafting), that thereby may augment their perceptions of job characteristics (demands and resources).

An alternative conceptualization of JD-R theory might acknowledge that strain and motivation represent beneficial and detrimental well-being outcomes (i.e., that are both aspects of a superordinate well-being construct) that are influenced by job characteristics and may influence or predict individuals' adaptive (e.g., job crafting) and maladaptive (e.g., self-undermining) behaviors that vary between individuals depending on contexts, individual differences, and/or other confounding variables. A brief comparison of job crafting and self-undermining behaviors may further elucidate this alternative conceptualization and the "two sides, same coin" argument. Current JD-R theory posits that job crafting behaviors are "the proactive changes employees make in their job demands and resources" (Bakker & Demerouti, 2017, p. 276). In other words, job crafting describes individuals' behaviors that positively impact and foster ideal job characteristics. Furthermore, these behaviors are conceptualized to include *task crafting* (i.e., positive changes to work tasks, such as pursuing more challenging demands and reducing hindrance demands), *relationship crafting* (positive changes to the type and/or frequency of social interactions, such as building new relationships or mentoring others), and *cognitive crafting* (positive changes to appraisal of one's work, such as focusing on its most meaningful aspects; Bakker & Demerouti, 2017). Conversely, current JD-R theory describes self-undermining behaviors as instances in which individuals "communicate poorly, make more mistakes and create more conflicts... are less able to manage their own emotions, and [are] more likely to encounter conflicts at work" (Bakker & Demerouti, p. 277). I posit that self-undermining behaviors simply reflect the *inverse* of job crafting, or behaviors that negatively impact job characteristics. For example, using similar terms as job crafting concepts, this could

include *task self-undermining* (negative changes to work tasks, such as increasing hindrance demands or neglecting challenging demands via increased mistakes or avoidant behaviors), *relationship self-undermining* (such as creating conflict via mismanaged emotions), or *cognitive self-undermining* (such as maladaptive beliefs or appraisals about one's work).

Although I reinforce prior assertions that this topic needs further research (e.g., Bakker & Demerouti, 2017; Schaufeli & Taris, 2014) and was not able to empirically test these conjectures with the variables of this study, simple changes to the computational model in this study may initially inform speculations about these concerns and their implications for future research. Specifically, by removing the conditional If-Then equation in the Strain function (i.e., respecifying the function to be Equation 3), the model no longer relies on the assumption that strain should only result and impact behavior when demands perceptions exceed desires. Rather, the simulation output simply shows a bi-directional process, which is contrary to current JD-R conceptualizations of dual processes. All other factors remaining constant, the loss spiral perpetuates as individuals' perceptions of demands exceed their desires. Conversely, when desires surpass expectations, the loss spiral inverts to yield a prolonged effect comparable to a gain spiral. Performance steadily increases, while demands decrease along with individuals' perceptions, strain outcomes, and self-undermining behaviors. This better reflects common human experiences of the fluctuations of these variables throughout daily life, and summarizes the general implications of this study; specifically, that (a) the theoretical premises of the self-undermining proposition were not supported in either the isolated or integrative computational and longitudinal results of this study, (b) these results were influenced by noteworthy methodological limitations of this study, but many of these limitations were also reflective and exemplary of broader limitations of JD-R theory, and (c) more research is

necessary that further tests the validity of JD-R theory propositions; incorporates the role of individual differences, time and other confounding or influential variables; and utilizes methodological and statistical techniques that are appropriate for assessing the intraindividual processes purported in JD-R theory.

Conclusion

The goal of this study was to test the self-undermining proposition in JD-R theory, which postulates that the influence of demands on strain may perpetuate and strengthen over time in a loss spiral via self-undermining behaviors, or behaviors that undermine one's performance. I tested the self-undermining proposition via two research methods. First, I developed and simulated a computational model of the variables and relationships in several JD-R model paths. Second, I developed four study hypotheses that exemplified the self-undermining proposition in academic contexts and tested the hypotheses with cross-lagged panel analyses and a repeated measures MANOVA of longitudinal data collected from undergraduate students over three time points. The results of each method were contradictory; the computational model portrayed an endless loss spiral, whereas the longitudinal study results did not provide supportive evidence for the self-undermining proposition. Although the incongruent results were influenced by the methodological limitations of this study (e.g., statistical power, measurement, temporal parameters, and the chosen computational and longitudinal methods), these limitations exemplified several broader limitations of JD-R theory such as its current conceptualizations of variables, paths, and processes that are inconsistent and inadequately incorporative of the role of individual differences and time. Overall, the study results did not support the self-undermining proposition and instead suggested that the overall JD-R theory is inviable and would benefit from

further research to robustly simulate, test, and respecify the purported constructs and relationships in the theoretical model.

Table 1.

Variables in the computational model.

Variable Name	Type of Variable	Time	Person/Environment
Key Variables			
perceptions	Endogenous	Time-varying	Person
Demands	Endogenous	Time-varying	Environment
Self-Undermining Behaviors	Endogenous	Time-varying	Person
Strain	Endogenous	Time-varying	Person
desires	Exogenous	Constant	Person
performance	Endogenous	Time-varying	Person
Other Variables			
appraisal	Exogenous	Constant	Person
initial demands	Exogenous	Constant	Environment
demands responsiveness	Exogenous	Constant	Environment
intentions	Exogenous	Constant	Person
resources	Exogenous	Constant	Person/Environment
cognitive ability	Exogenous	Constant	Person

Note. Dynamic variables are capitalized.

Table 2.

Labels, types, and equations of final computational model variables in Vensim®.

Variable	Type	General Equation	Vensim® Equation
Strain	Level	If (perceptions – desires) > 0, then $Strain_t = \int \left((perceptions - desires) \times \frac{1}{resources} \right) dt$ Else, $Strain = 0$	Strain = INTEG(IF THEN ELSE(perceptions – desires > 0, (perceptions – desires), 0) * resources initial value = 0
desires	Constant	$desires = 0$	desires = 0
resources ^a	Constant	$resources = 1$	resources = 1
Self-Undermining Behaviors	Level	$Self-Undermining\ Behaviors_t = \int \left(\frac{Strain \times intention}{2} \right) dt$	Self-Undermining Behaviors = INTEG(Strain * intention) initial value = 0
intention ^a	Constant	$intention = 1$	intention = 1
Demands	Level	$Demands_t = \int (Self-Undermining\ Behaviors \times demands\ responsiveness) dt$	Demands = INTEG(Self-Undermining Behaviors * demands responsiveness) initial value = initial demands
initial demands	Constant	$initial\ demands = 1$	initial demands = 1
demands responsiveness ^a	Constant	$demands\ responsiveness = 0.1$	demands responsiveness = 0.1
perceptions ^a	Auxiliary	$perceptions = Demands + appraisal$	perceptions = Demands + appraisal
appraisal ^a	Constant	$appraisal = 0$	appraisal = 0
performance	Level	$performance_t = \int \left(\frac{-Strain + cognitive\ ability}{2} \right) dt$	Academic Performance = INTEG(-Strain + cognitive ability) initial value = initial performance
cognitive ability ^a	Constant	$cognitive\ ability = 0$	cognitive ability = 0

Notes. Constant equations represent initial values specified in the model. ^aIndicates variables added during model building.

Table 3.

Longitudinal data collection schedule.

Wave	Sample	
	Western	Southern
Wave 1		
Survey open	Monday 4/1	Thursday 3/28
Reminder email	Thursday 4/4	Monday 4/1
Survey close	Monday 4/8	Thursday 4/4
Wave 2		
Survey open	Monday 4/15	Thursday 4/11
Reminder email	Thursday 4/18	Monday 4/15
Survey close	Monday 4/22	Thursday 4/18
Wave 3		
Survey open	Monday 4/29	Tuesday 4/23
Reminder email	Thursday 5/2	Wednesday 4/24
Survey close	Monday 5/6	Thursday 4/25

Table 4.

Means, standard deviations, and correlations for all study variables

	M	SD	1	2	3	4	5	6	7	8	9
1. T1-Demands	3.17	0.87	.86								
2. T2-Demands	3.19	0.90	.74**	.89							
3. T3-Demands	3.26	0.92	.71**	.78**	.91						
4. T1-Strain	3.81	0.76	.48**	.43**	.42**	.78					
5. T2-Strain	3.81	0.71	.44**	.49**	.47**	.63**	.79				
6. T3-Strain	3.81	0.79	.46**	.49**	.54**	.63**	.70**	.84			
7. T1-SUB	2.78	0.88	.19**	.28**	.27**	.36**	.32**	.30**	.82		
8. T2-SUB	2.73	0.88	.26**	.29**	.25**	.25**	.33**	.30**	.67**	.85	
9. T3-SUB	2.79	0.84	.21**	.32**	.33**	.29**	.36**	.38**	.64**	.73**	.83
10. T1-Grade	4.21	0.84	-.03	-.06	-.05	.07	-.00	.05	-.28**	-.17*	-.18**
11. T2-Grade	4.19	0.87	-.05	-.02	.01	.04	-.02	.02	-.28**	-.22**	-.19**
12. T3-Grade	4.12	0.88	-.10	-.06	-.10	.02	-.05	-.02	-.27**	-.15*	-.21**
13. T1-GPA	4.72	1.04	-.04	.01	.04	-.03	-.05	.05	-.31**	-.22**	-.23**
14. T2-GPA	4.79	0.99	-.07	-.05	-.04	.00	-.05	.00	-.34**	-.28**	-.19**
15. T3-GPA	4.80	0.99	-.14*	-.10	-.05	-.03	-.05	.01	-.32**	-.16*	-.22**

Notes. 213 < N < 341. Values on the diagonal indicate scale reliabilities (omega). Grade and GPA were measured on a 1-6 scale.

SUB = Self-Undermining Behaviors; T1 = Time 1; T2 = Time 2; T3 = Time 3. ** $p < .01$; * $p < .05$.

Table 4 (cont'd).

Means, standard deviations, and correlations for all study variables

	10	11	12	13	14	15
10. T1-Grade	–					
11. T2-Grade	.90**	–				
12. T3-Grade	.85**	.90**	–			
13. T1-GPA	.66**	.67**	.68**	–		
14. T2-GPA	.66**	.68**	.69**	.86**	–	
15. T3-GPA	.64**	.65**	.67**	.81**	.86**	–

Notes. 213 < N < 341. Values on the diagonal indicate scale reliabilities (omega). Grade and GPA were measured on a 1-6 scale. T1 = Time 1; T2 = Time 2; T3 = Time 3. ** p < .01; * p < .05.

Table 5.

Fit statistics and chi-square difference tests of nested models in cross-lagged analyses

Model	χ^2	df	p	Model Fit				Model Comparison		
				RMSEA	CFI	TLI	SRMR	$\Delta\chi^2$	Δdf	p
Full proposition										
M1 – Stability	1045.09	777	.000	0.03	0.96	0.96	0.06	–	–	–
M2 – Causal	1035.65	768	.000	0.03	0.96	0.96	0.06	9.45	9	.397
M3 – Reversed causal	1034.43	768	.000	0.03	0.96	0.96	0.06	10.66	9	.300
M4 – Reciprocal	1019.67	759	.000	0.03	0.96	0.96	0.05	25.42	18	.114
Without performance										
M1 – Stability	890.34	668	.000	0.03	0.97	0.96	0.06	–	–	–
M2 – Causal	880.19	659	.000	0.03	0.97	0.96	0.05	10.15	9	.338
M3 – Reversed causal	880.62	659	.000	0.03	0.97	0.96	0.06	9.72	9	.374
M4 – Reciprocal	864.07	650	.000	0.03	0.97	0.96	0.05	26.28	18	.094

Notes. χ^2 , chi-square; *df*, degrees of freedom; RMSEA, root mean square error of approximation; CFI, comparative fit index; TLI, Tucker-Lewis Index. Model comparison statistics are chi-square difference ($\Delta\chi^2$) test results of nested models compared to the stability model (M1).

Table 6.
Maximum likelihood estimates of reciprocal effects

T1-T2 Predictors	T2-T3 Outcomes							
	T2 Dem.	T3 Dem.	T2 Strain	T3 Strain	T2 SUB	T3 SUB	T2 Perf.	T3 Perf.
M4 (Full proposition)								
T1 Demands	<i>.79</i>		<i>.06</i>	<i>.08</i>	.20*	-.37**		
T2 Demands		<i>.80</i>		<i>.02</i>		.28*		
T1 Strain	<i>-.04</i>	<i>.13</i>	<i>.69</i>		-.20*	.27*	<i>-.03</i>	<i>-.02</i>
T2 Strain		<i>-.03</i>		<i>.79</i>		<i>-.11</i>		<i>.02</i>
T1 Self-Undermining	<i>.11</i>	<i>.00</i>	<i>.03</i>	<i>.11</i>	<i>.83</i>			
T2 Self-Undermining		<i>-.03</i>		<i>-.12</i>		<i>.78</i>		
T1 Performance							<i>.88</i>	
T2 Performance								<i>.88</i>
M4 (without perf.)								
T1 Demands	<i>.80</i>		<i>.07</i>	<i>.08</i>	.20*	-.37**		
T2 Demands		<i>.80</i>		<i>.02</i>		.30*		
T1 Strain	<i>-.07</i>	<i>.13</i>	<i>.69</i>		-.21*	.28*		
T2 Strain		<i>-.03</i>		<i>.79</i>		<i>-.13</i>		
T1 Self-Undermining	.14*	<i>.02</i>	<i>.03</i>	<i>.14</i>	<i>.83</i>			
T2 Self-Undermining		<i>-.04</i>		<i>-.13</i>		<i>.78</i>		

Notes. $N = 429$. * $p < .05$; ** $p < .01$. Significant reciprocal effects are bolded. Autoregressive path coefficients are italicized.

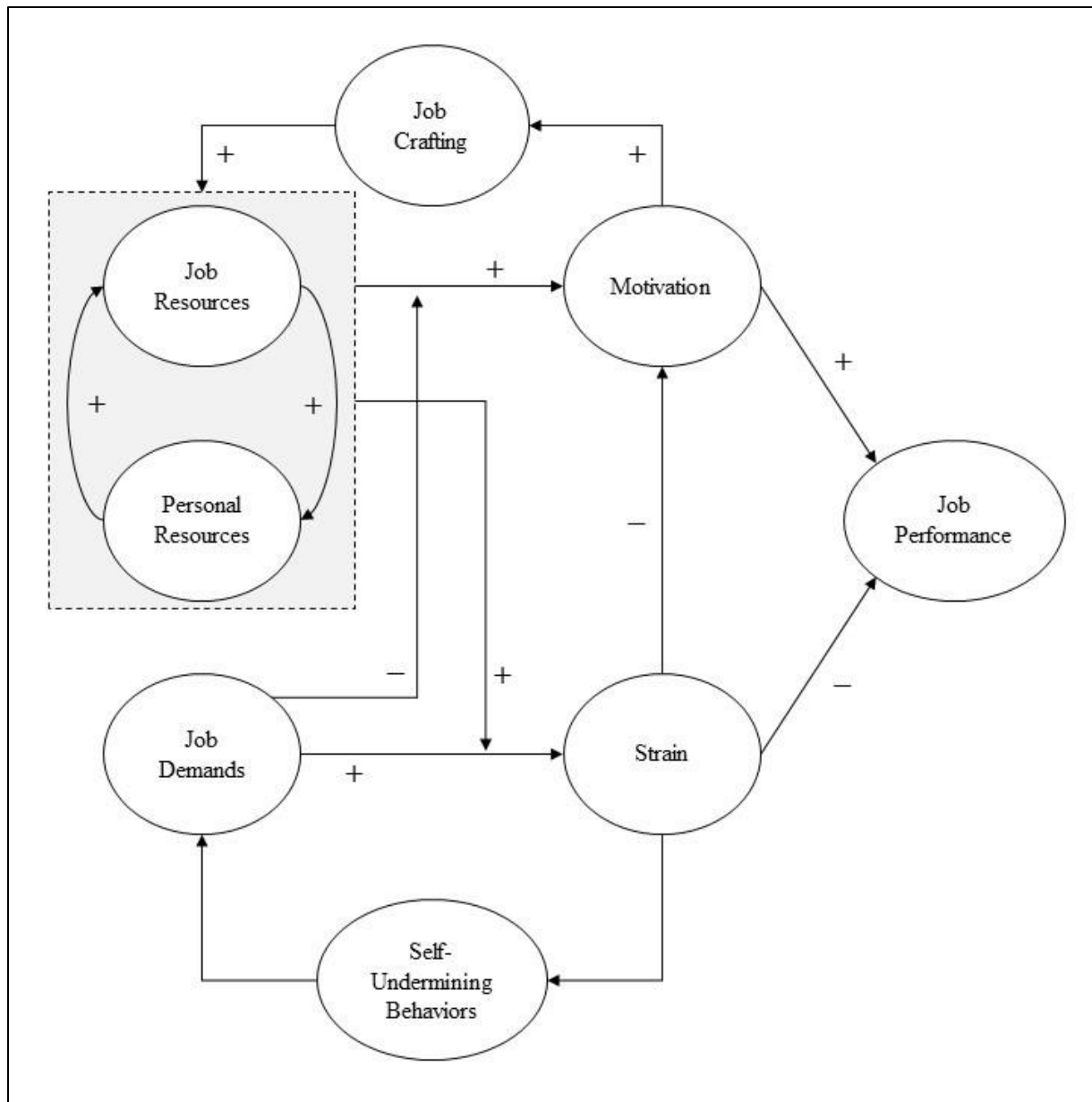


Figure 1. The current conceptual model of Job Demands-Resources Theory as reported by Bakker and Demerouti (2017).

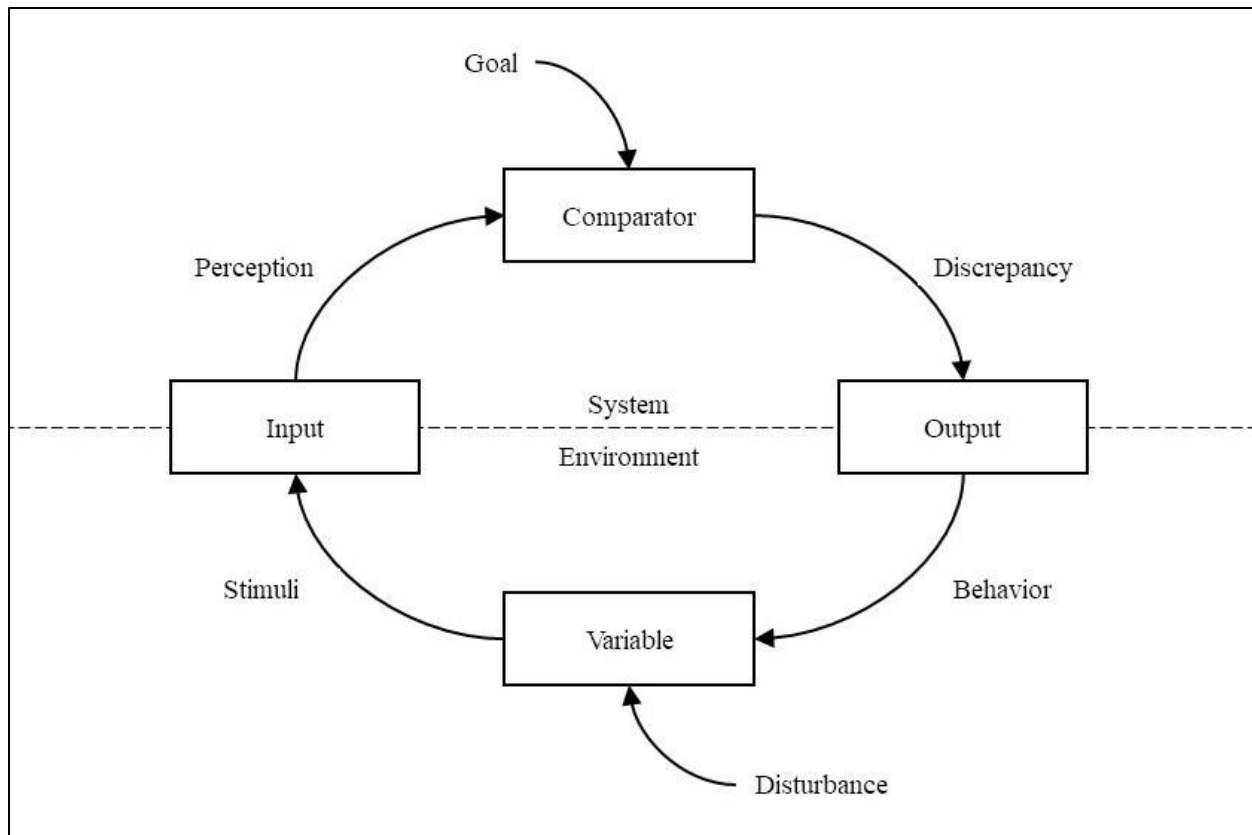


Figure 2. A depiction of a basic computational model based in control theory as reported by Vancouver et al. (2005).

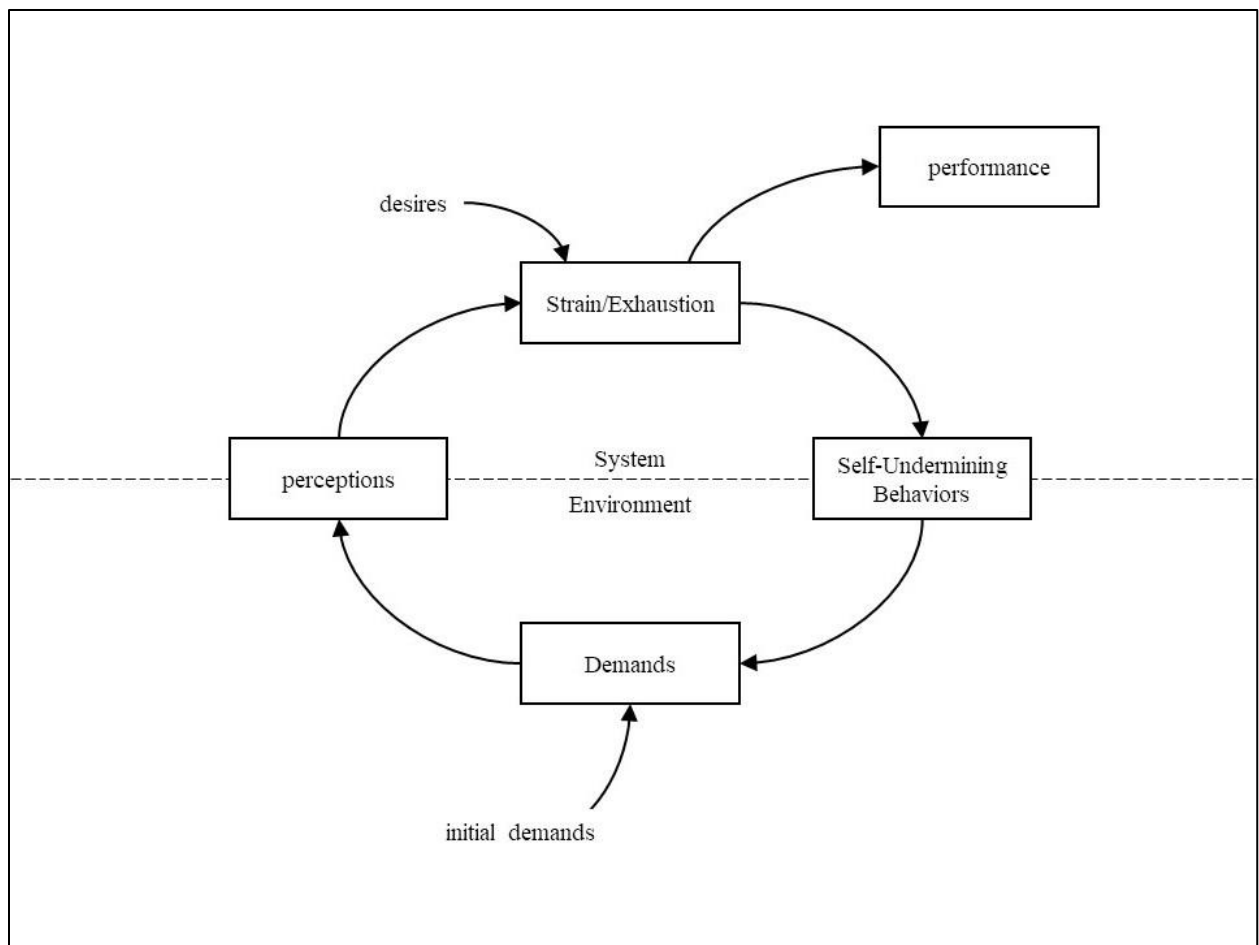


Figure 3. The initial computational model of the self-undermining proposition.

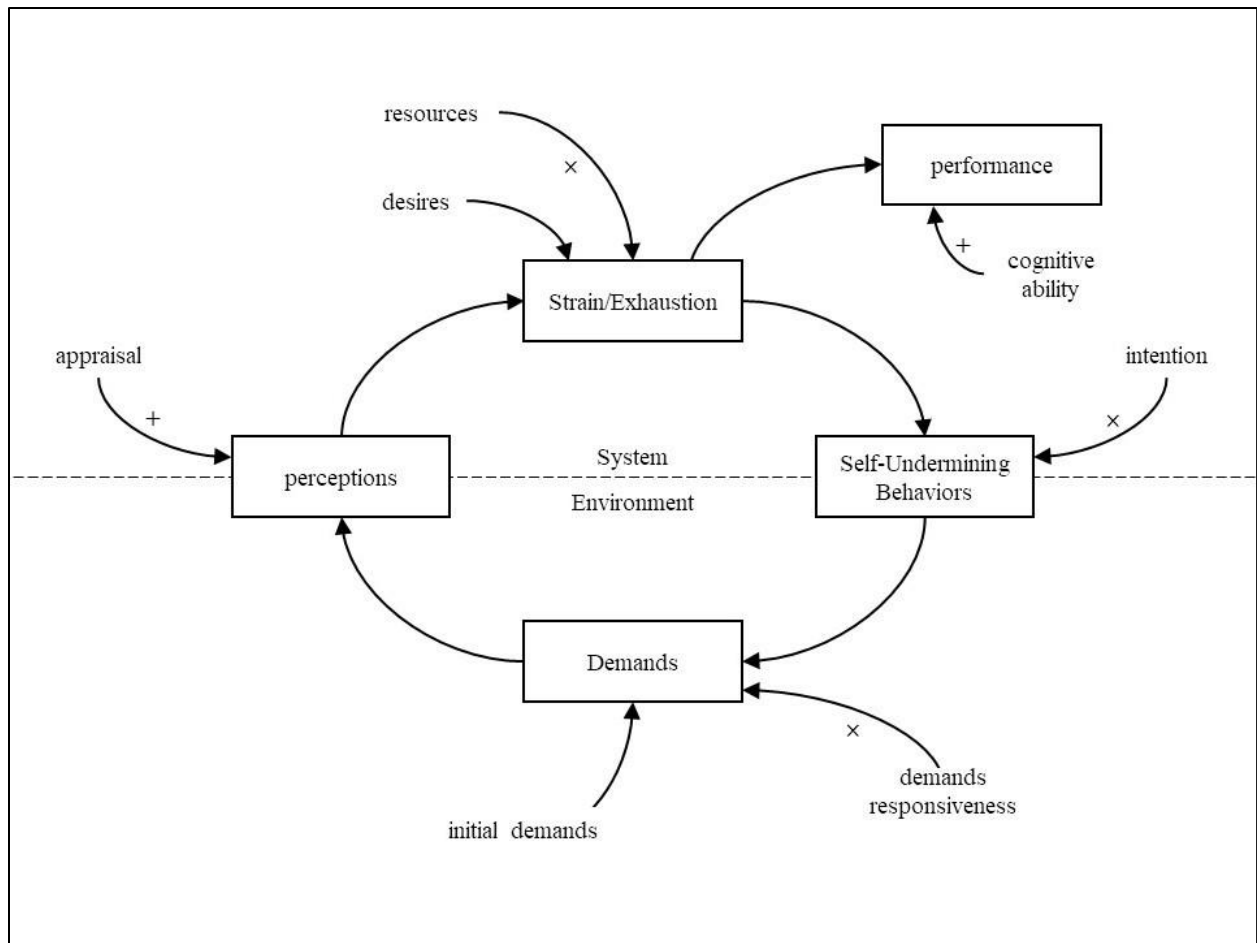


Figure 4. The final computational model of the self-undermining proposition.

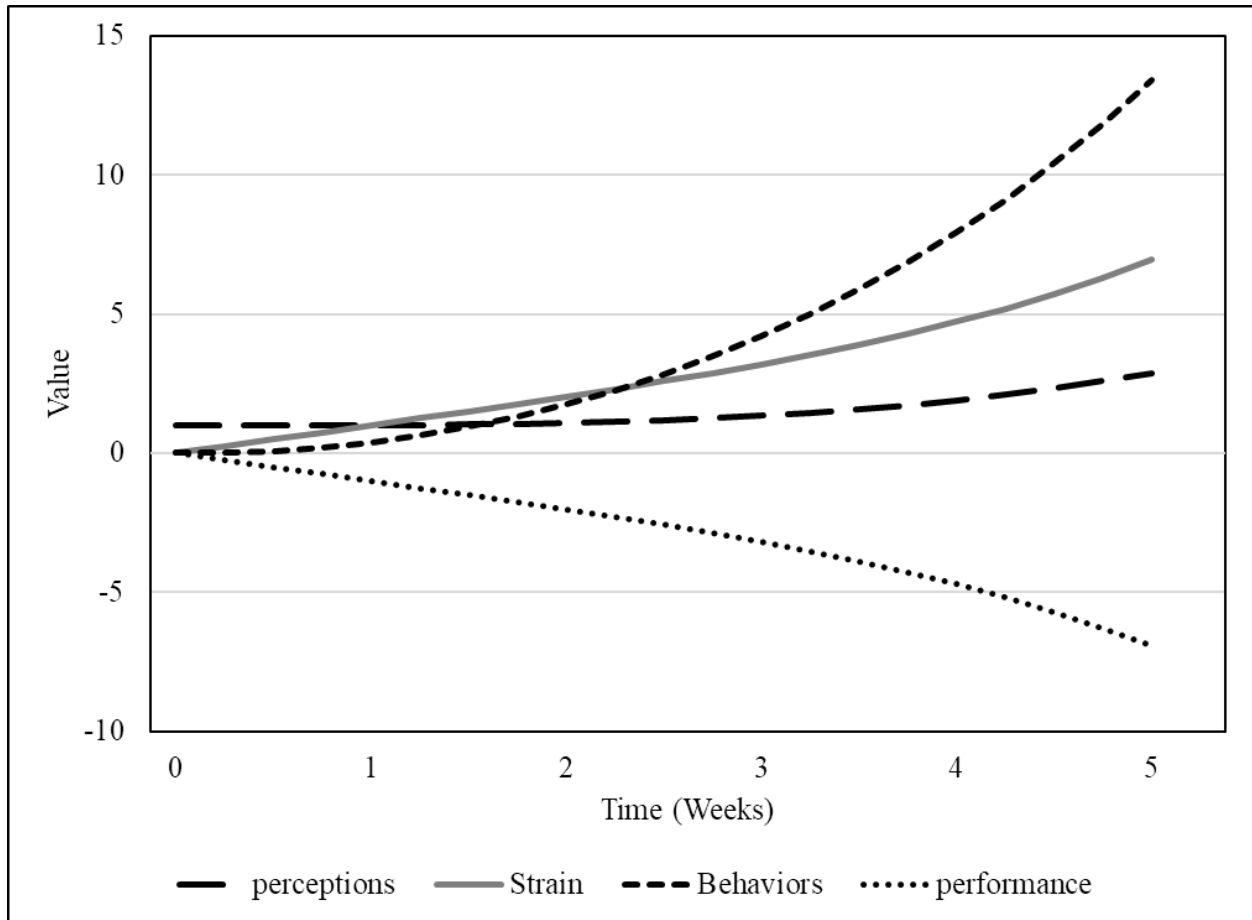


Figure 5. Computational model simulation output with initial specifications.

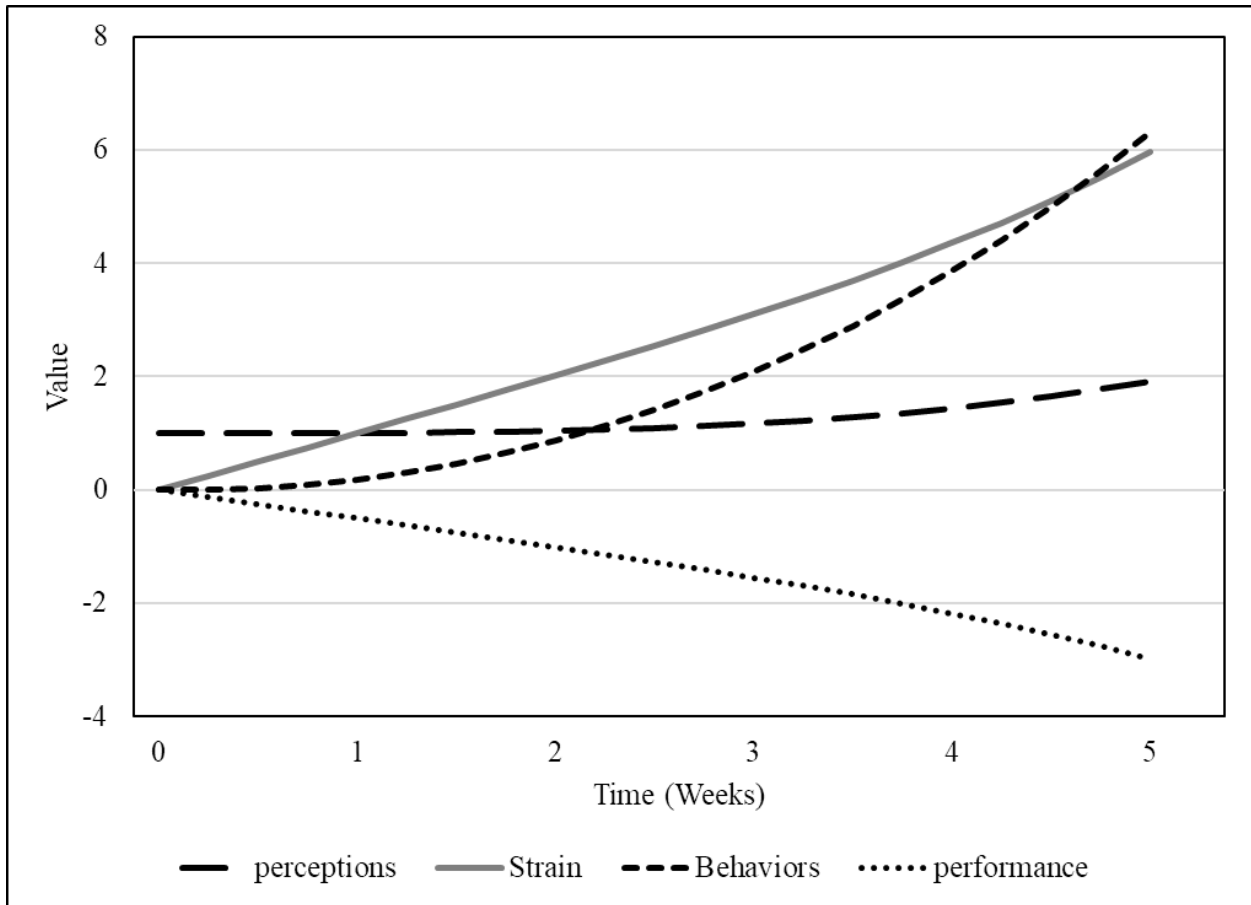


Figure 6. Computational model simulation output with final specifications.

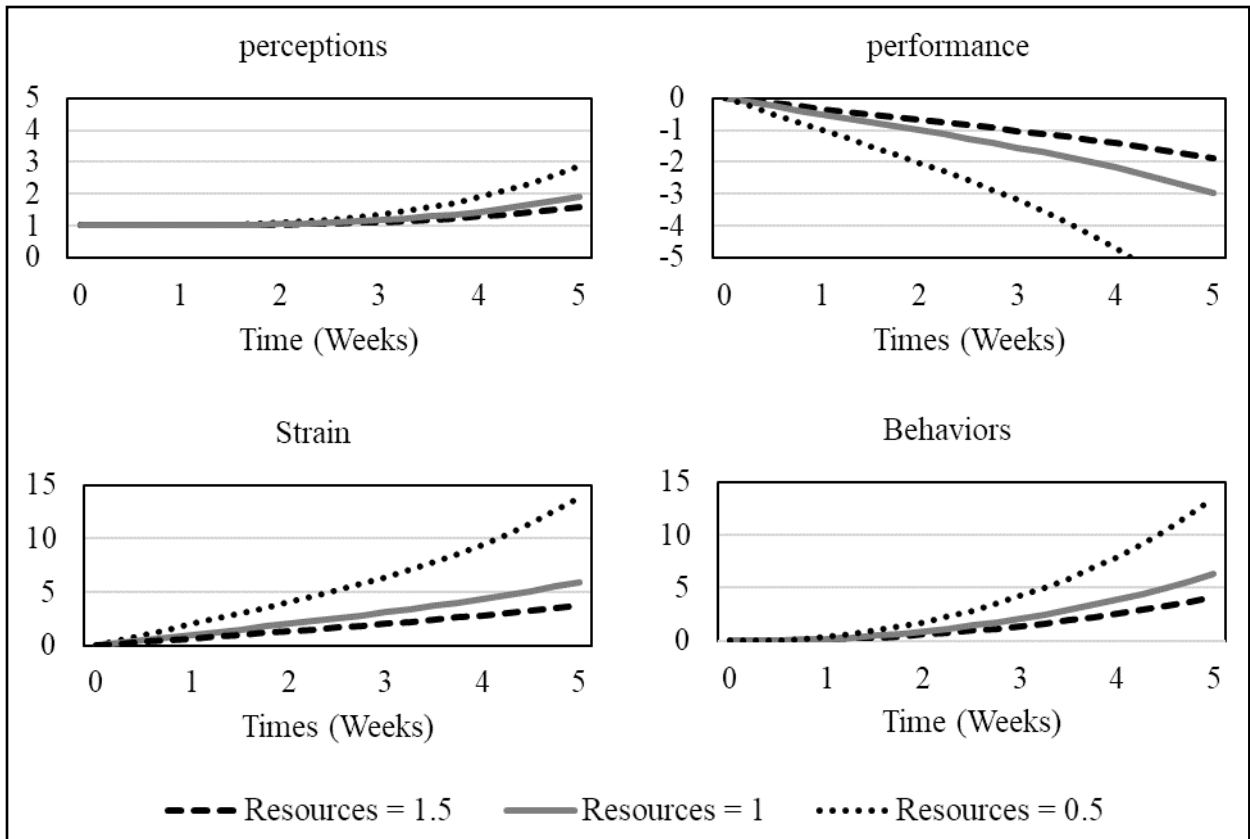


Figure 7. Computational model simulation output from sensitivity analyses at higher and lower starting values of resources.

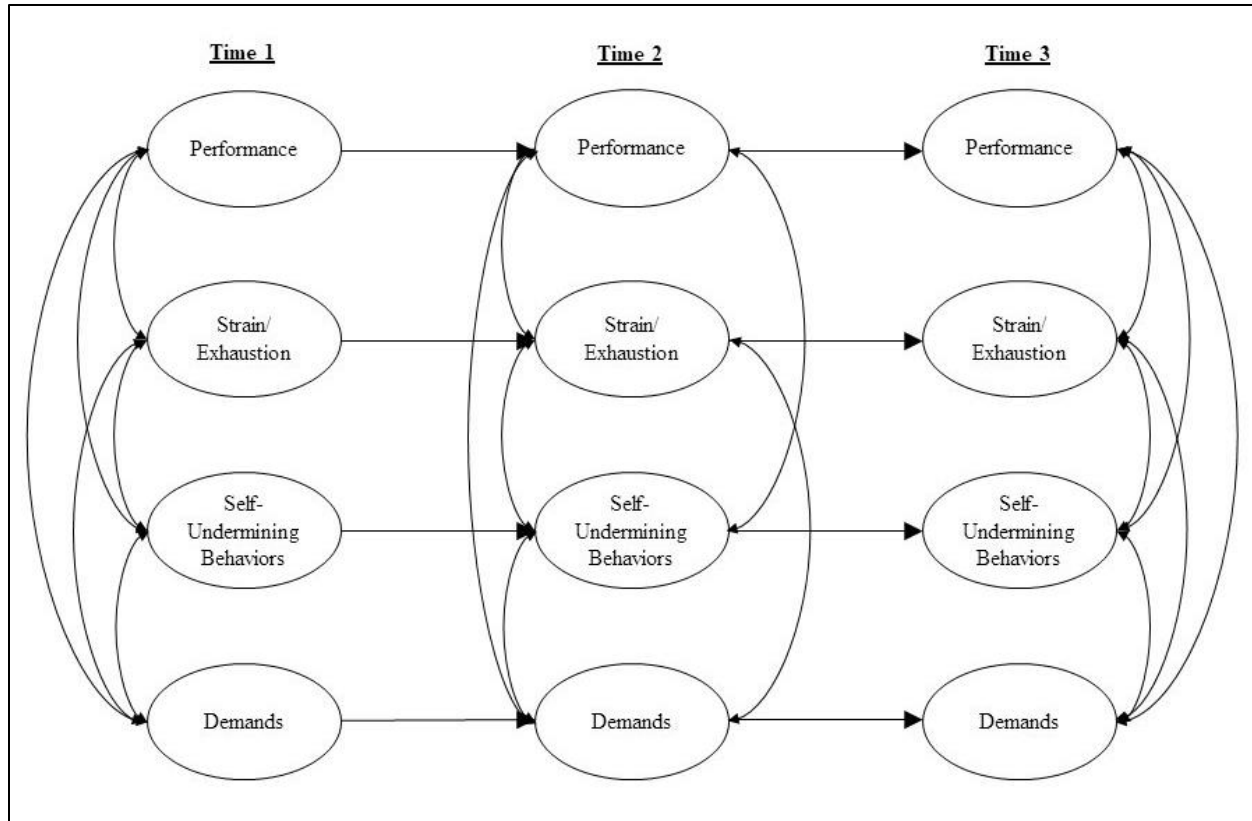


Figure 8. Autoregressive paths and synchronous correlations of the stability model (M1) in cross-lagged analyses.

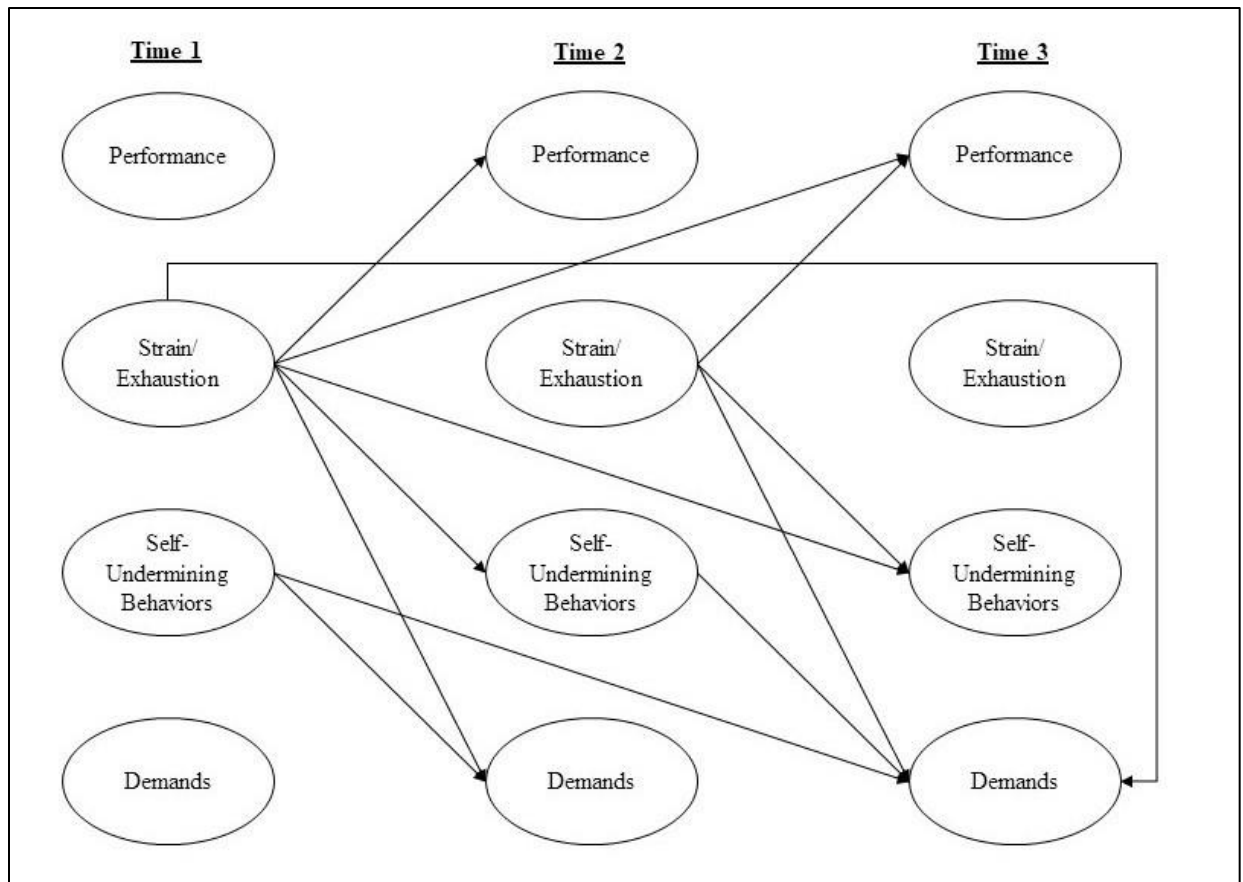


Figure 9. Additional paths in the causal model (M2) in cross-lagged panel analyses.

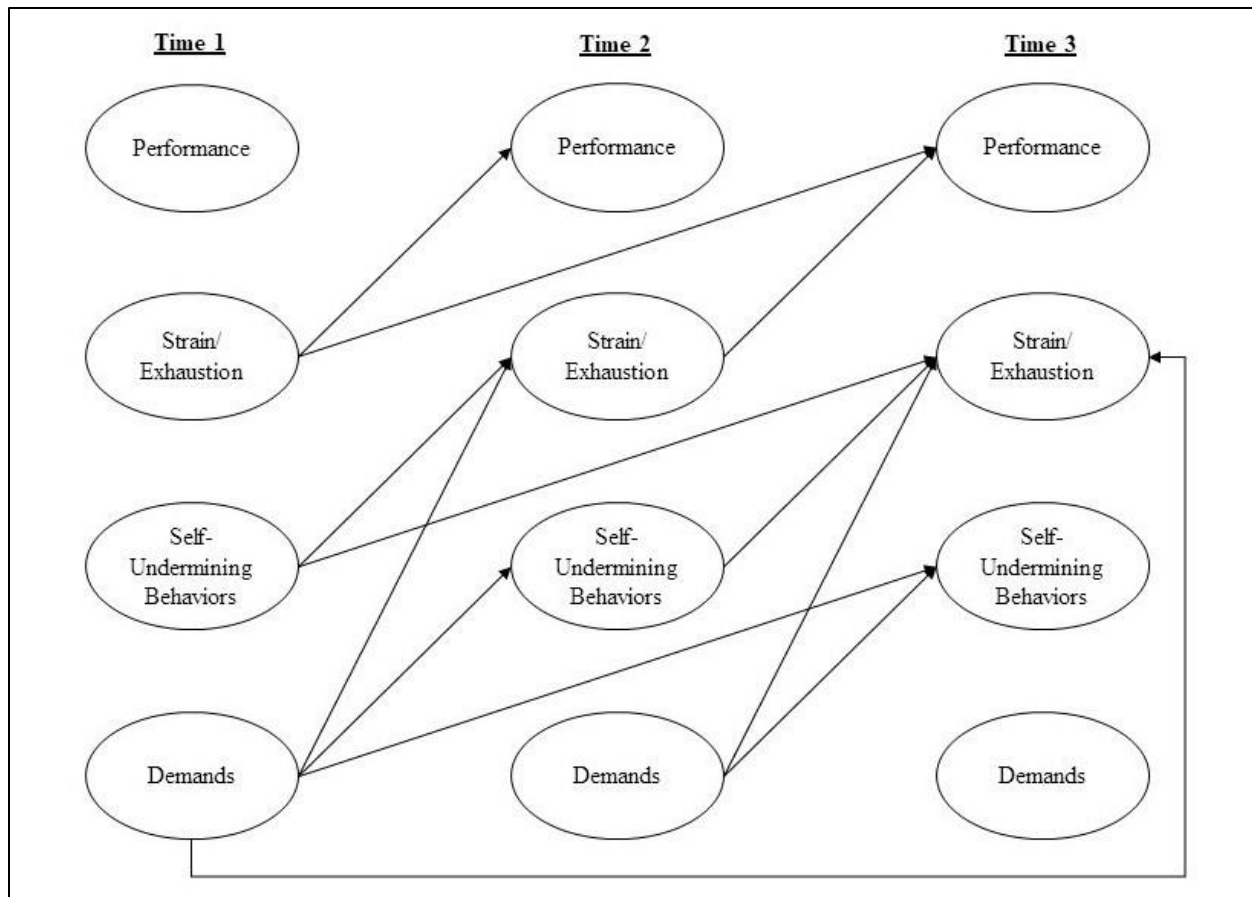


Figure 10. Additional paths in the reversed causal model (M3) in cross-lagged panel analyses.

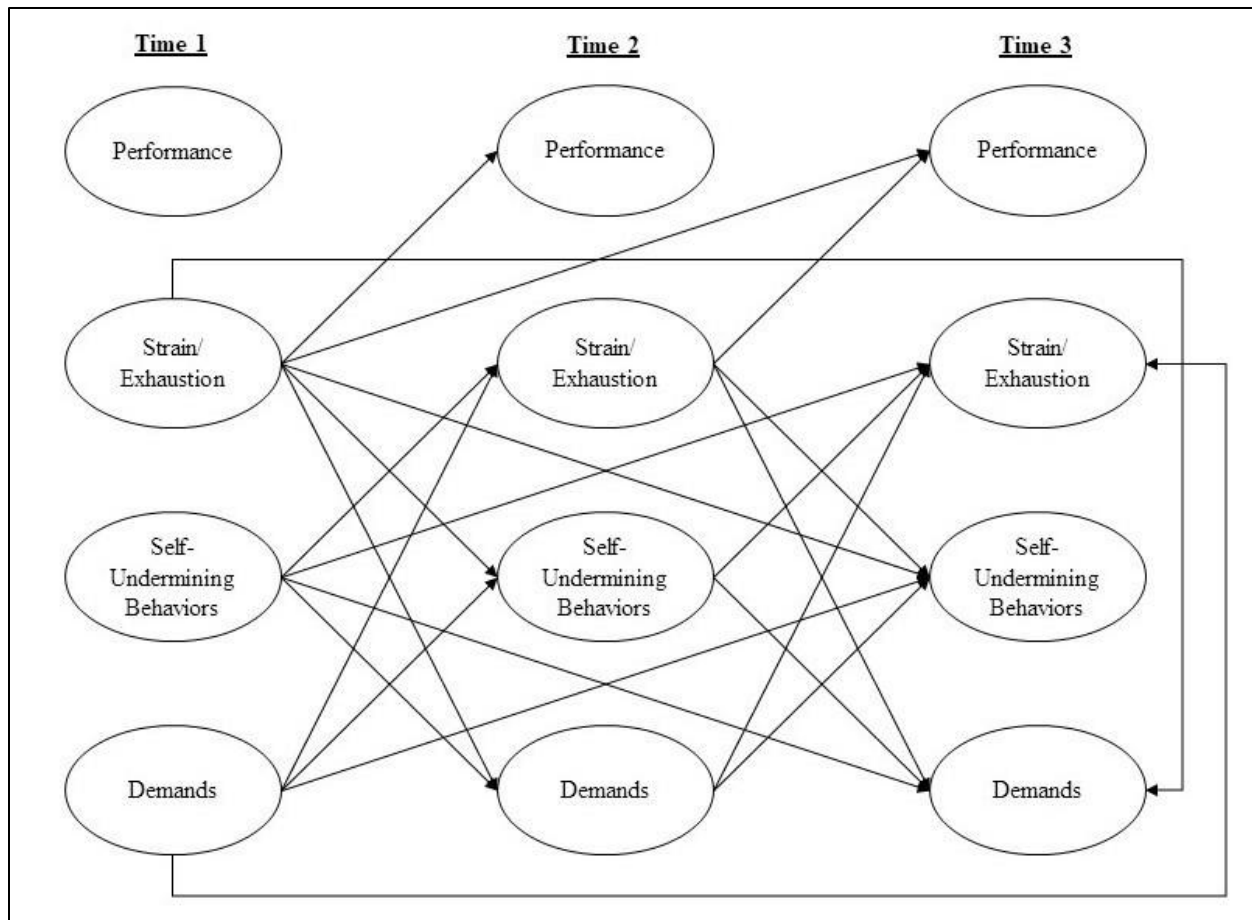


Figure 11. Additional paths in the reciprocal model (M4) in cross-lagged panel analyses.

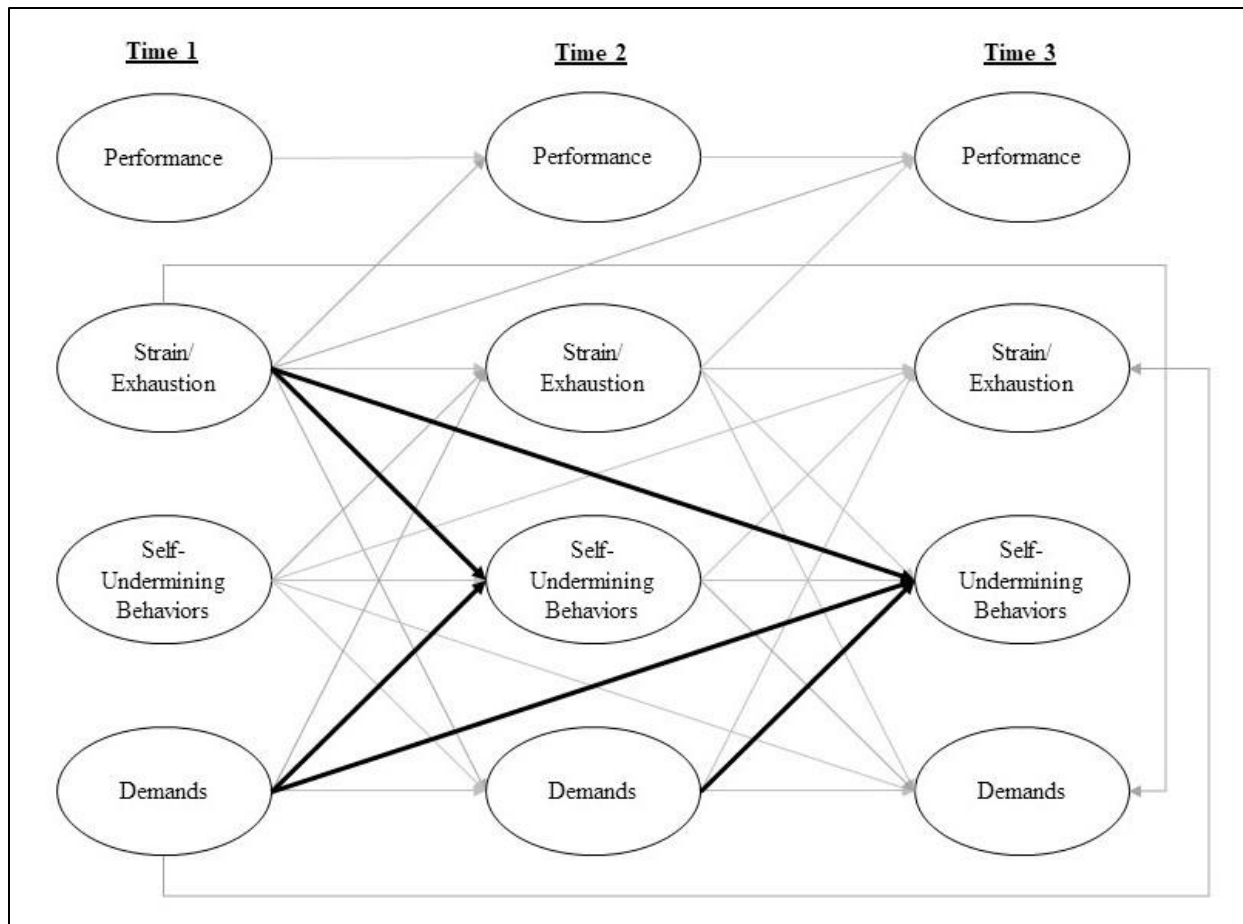


Figure 12. Significant paths in the reciprocal model (M4) for the full self-undermining proposition model test.

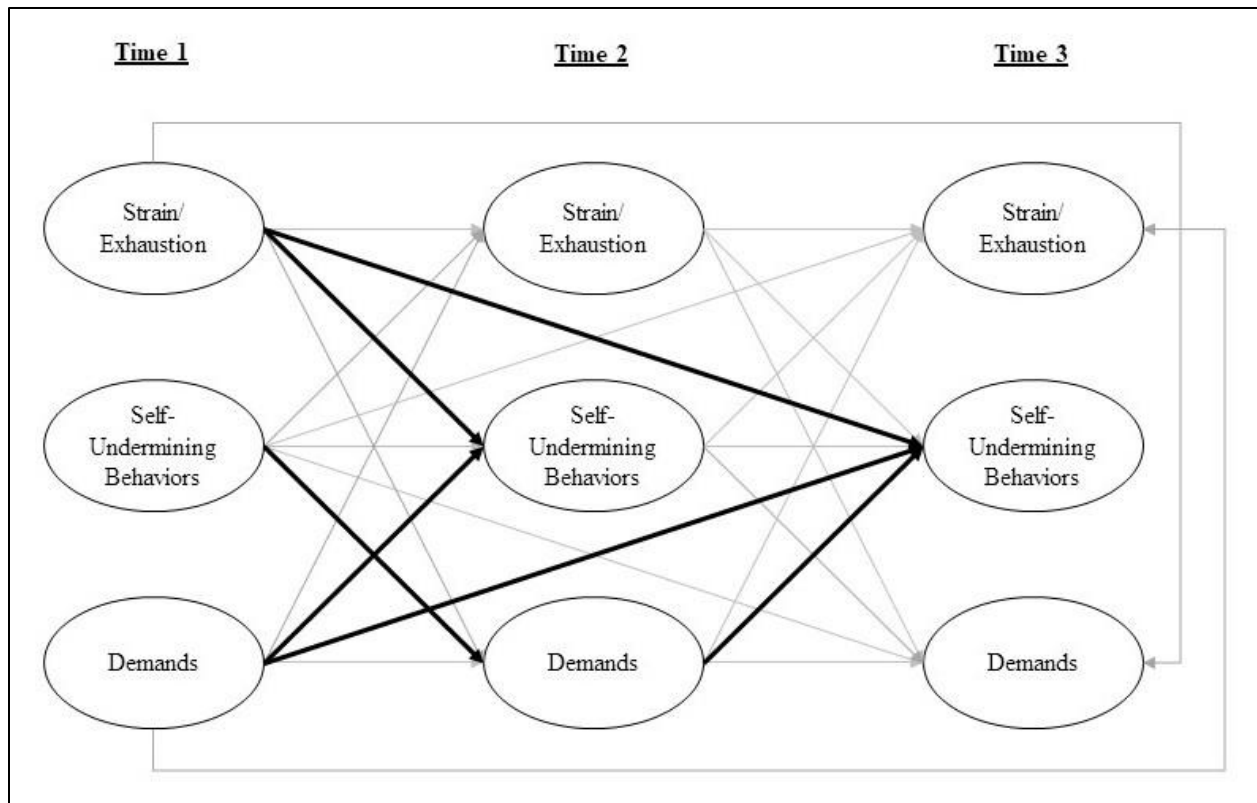


Figure 13. Significant paths in the reciprocal model (M3) for the self-undermining proposition test without performance.

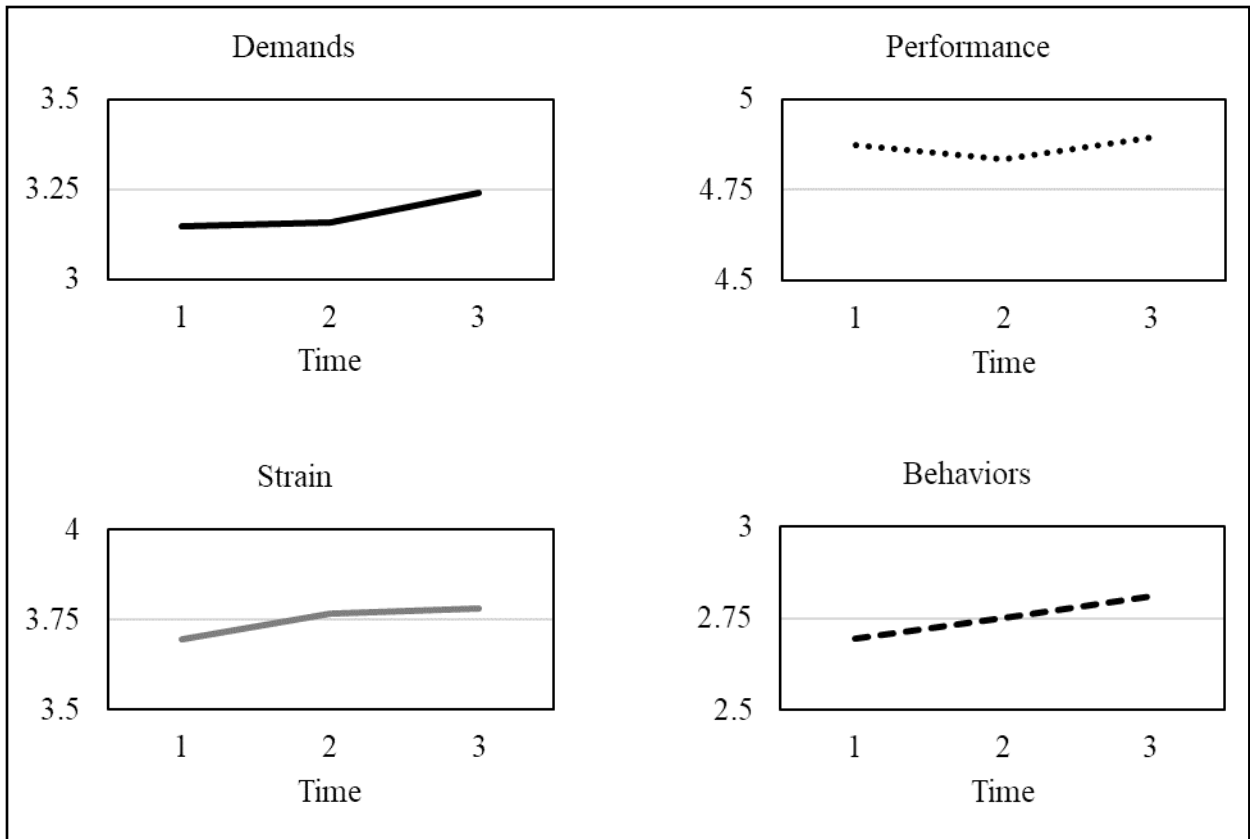


Figure 14. Plots of DV estimated marginal means over time points in RM MANOVA. Performance was rated on a 1-6 scale; demands, strain, and self-undermining behaviors were on a 1-5 scale.

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Appendix A

Additional Time 1 Questions

Qualifying Question

1. Are you currently an enrolled student at [University]?
 - Yes
 - No

Unique Identifier (to link survey responses across timepoints)

2. Please create a unique identifier that only you will know as follows:

Second letter of your first name (e.g., “e”): _____

The two digits of the day [01 through 31] of your birthday: _____

Last letter of your last name (e.g., “s”): _____

Last two digits of your address (e.g., “01”): _____

3. Please write the combined unique identifier you created (e.g., e13s01): _____

Demographics

Please answer the following questions.

4. What is your gender?
 - Male
 - Female
 - Other (please specify: _____)
 - Prefer not to disclose
5. What is your age, in years? (please type a two-digit number, e.g., 30): _____
6. What is your race/ethnicity? (Please mark all that apply)
 - White/Caucasian
 - Black/African-American
 - Hispanic/Latino
 - Native American/Alaska Native
 - Asian/Asian-American
 - Hawaiian/Pacific Islander
 - Two or more races
 - Other (please specify: _____)

7. What is your highest level of education?
- High school or GED
 - Some college
 - 2 year degree
 - 4-year degree
 - Master's degree
 - Doctoral degree
 - Professional degree (e.g, J.D.)
 - Other (please explain: _____)
8. What is your enrollment status?
- Full-time student
 - Part-time student
9. What is your class standing?
- Freshman
 - Sophomore
 - Junior
 - Senior
 - Other (please specify: _____)
10. What is your major or area of study?

Job Information

11. Do you currently have a job?
- Yes
 - No
12. How many jobs do you currently have?
- 0
 - 1
 - 2
 - 3+
13. How many hours do you work for your employer in a typical week?

Appendix B

Additional Time 2 and Time 3 Survey Questions

1. This is the second survey you have completed in this study. In the first survey, which you completed approximately two weeks ago, you answered questions about your classes at the time. Has your course enrollment changed since the first survey? (e.g., dropping or adding a course)
 - No, my course schedule is the same
 - Yes, my course schedule has changed
2. How has your course schedule changed? Please explain: _____

Appendix C

Quantitative Workload Inventory (adapted from Spector & Jex, 1997)

Instructions:

The following questions will ask you about your day-to-day experiences as a student. Please use the following scale to answer these questions.

1. How often does your schoolwork require you to work very fast?*
 2. How often does your schoolwork require you to work very hard?
 3. How often does your schoolwork leave you with little time to get things done?*
 4. How often is there a great deal to be done?*
 5. How often do you have to do more work than you can do well?
-

Note. Items were rated on a 1 to 5 scale where 1 = Less than once per month or never, 2 = Once or twice per month, 3 = Once or twice per week, 4 = Once or twice per day, and 5 = Several times per day. *indicates items retained in the final scale.

Appendix D

Exhaustion sub-scale of the Oldenburg Burnout Inventory
(adapted from Demerouti, Bakker, Vardakou, & Kantas, 2003)

Instructions:

Please use the following scale to rate the extent to which you agree or disagree with each statement.

1. There are days when I feel tired before I begin my studies. (R)*
 2. After school, I tend to need more time than in the past in order to relax and feel better. (R)*
 3. I can tolerate the pressure of my schoolwork very well.
 4. During my studies, I often feel emotionally drained. (R)*
 5. After studying, I have enough energy for my leisure activities.
 6. After my studies, I usually feel worn out and weary. (R)*
 7. Usually, I can manage the amount of my schoolwork well.
 8. When I study, I usually feel energized.
-

Note. Items were rated on a 1 to 5 scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree. (R) indicates a reverse coded item. *indicates items retained in the final scale.

Appendix E

Self-Undermining Behaviors Scale

(adapted and expanded from Bakker, 2016; Bakker & Wang, 2016)

Definition (adapted from Bakker, 2016): behaviors of students under stress that can impair their own functioning and worsen their working conditions; i.e., student behaviors that create obstacles that may undermine or hinder the individual's academic performance

Instructions and Items:

Please use the following scale to rate the extent to which you agree or disagree with each statement.

1. I asked for help when I needed it. (R)
2. I worked ahead in my classes. (R)
3. I always attended class. (R)
4. I avoided asking for help.
5. I often procrastinated.
6. I skipped class.
7. I forgot important due dates in my courses (e.g., due dates, exam dates, etc.).
8. I did things that hurt my grades.*
9. I created conflict with my classmates.
10. I didn't take care of myself (e.g., nutrition, exercise, sleep, etc.).
11. I fell behind in my schoolwork.*
12. I forgot about course requirements.*
13. I didn't work as hard as I should.
14. I put off my schoolwork.*
15. I got enough sleep. (R)
16. I crammed for tests.
17. I was disorganized.*
18. I finished all of my schoolwork. (R)
19. I didn't pay attention in class.
20. I made a lot of simple mistakes in my schoolwork.
21. I made things more confusing.
22. I created more stress for myself.
23. I got things done on time. (R)
24. I rarely forgot about things. (R)
25. I turned in my schoolwork on time. (R)
26. I let my schoolwork pile up.
27. I made careless mistakes on my schoolwork.
28. I didn't study when I should have.
29. I slept less to complete my schoolwork on time.

Note. Items were rated on a 1 to 5 scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree. (R) indicates a reverse coded item. *indicates items retained in the final scale.

Appendix F

Academic Performance Measures (adapted from Morehead, Rhodes, & DeLozier, 2015)

1. For what course are you participating in this study?
2. What is your current grade in [Q1 course]?
 - A (between 90-100)
 - B (between 80-89)
 - C (between 70-79)
 - D (between 60-69)
 - F (59 or below)
3. What is your current GPA for the Spring 2019 semester?
 - 0.0 – 1.6
 - 1.7 – 2.1
 - 2.2 – 2.6
 - 2.7 – 3.1
 - 3.2 – 3.6
 - 3.7 – 4.0