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Giordano, C., & Mercado, B. K. (2023). Cyberloafing: Investigating the Importance and Implications of New and Known Predictors. *Collabra: Psychology*, *9*(1). https://doi.org/10.1525/collabra.57391

Organizational Behavior

Cyberloafing: Investigating the Importance and Implications of New and Known Predictors

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Keywords: counterproductive work behaviors, interpersonal conflict, cognitive ability, boredom, cyberloafing

https://doi.org/10.1525/collabra.57391

Collabra: Psychology

Vol. 9, Issue 1, 2023

Cyberloafing occurs when employees use technology to loaf instead of work. Despite mounting organizational concern and psychological research on cyberloafing, research provides little actionable guidance to address cyberloafing. Therefore, the present study builds on previous cyberloafing investigations in three primary ways. First, we utilize a person-situation framework to compare personological and situational construct domains. Second, we extend the cyberloafing nomological network by investigating previously unexamined, yet powerful, predictors. Third, we employ a multivariate approach to identify the most important cyberloafing antecedents. From seven cyberloafing constructs, we found that boredom, logical reasoning, and interpersonal conflict were the most important correlates. Our results highlight novel, important predictors of cyberloafing and allow us to provide empirically-based recommendations for developing cyberloafing interventions.

Cyberloafing occurs when employees engage in technologically-mediated loafing behaviors instead of work-related behaviors (Pindek et al., 2018) and is one of the most common ways employees waste time at work (Kim & Christensen, 2017). Udemy (2018) reported that 62% of employees wasted about 60 minutes of worktime, per day, through personal phone use alone. *Forbes* (Conner, 2015), among other popular press outlets, also routinely asserts that employee cyberloafing has hit an alarming critical mass. Echoing these sentiments, the academic literature has demonstrated both the prevalence and severity of cyberloafing at work (e.g., Black et al., 2013; Khansa et al., 2018).

To address growing organizational concern, researchers must determine which cyberloafing predictors are the most promising avenues for organizational action. Consequently, investigations into predictors have proliferated; a quantitative review culled over 600 effect sizes exploring thirty-nine correlates to summarize the nomological network of cyberloafing (Mercado et al., 2017). Although cyberloafing has been broadly examined, this body of work is shallow, indicated by few samples and studies measuring each relationship. Moreover, the cyberloafing domain is typically studied via a piecemeal approach—studies often explore only one or a small subset of interrelated predictors (e.g., overqualification, Cheng et al., 2018; employee monitoring, Glassman et al., 2015; boredom, Pindek et al., 2018). This approach precludes investigations into which of a variety of intercorrelated predictors *most* merits attention. Compounding this problem, the Mercado et al. (2017) review illustrates that several of the weakest cyberloafing predictors were also the most frequently studied. Evidently, scientists and practitioners seeking to understand and reduce cyberloafing would benefit from more direct guidance identifying its most influential and important predictors.

This study aims to address this literature gap and extend the cyberloafing literature in three ways. First, we employ a person-situation framework, drawing upon theoretical (e.g., field theory, Burnes & Cooke, 2013; Lewin, 1939; see also, Marcus & Schuler, 2004) and empirical work across predictor domains, to identify potentially important classes of cyberloafing antecedents. This person-situation approach allows us to investigate whether personological or situational constructs are more impactful predictors of cyberloafing (RQ1). Second, in identifying antecedents, we expand the known nomological network of cyberloafing to include impactful, previously unexamined predictors. Third, we employ the multivariate dominance analysis procedure (Budescu, 1993; see also, Thomas et al., 2014) to address our overarching research question (RQ2): Which are the most important variables for predicting cyberloafing? Ultimately, our findings yield implications for prospective intervention strategies in firms plagued with excessive cy-

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berloafing. In what follows, we provide an overview of the cyberloafing domain and describe our rationale for selecting constructs for this variable importance study.

Cyberloafing

The definition of cyberloafing (cf. Lim, 2002) that we employ—employees' technologically-mediated nonwork behaviors when they should be working (Pindek et al., 2018)—reflects the modern, multimodal nature of cyberloafing. Despite recent, widespread interest in cyberloafing, this developing literature still has many gaps pertaining to antecedents and theoretical mechanisms. Consequently, in trying to determine the best predictors of cyberloafing, we also consulted well-established literatures from related behavioral domains. The most notable is that of counterproductive work behaviors (CWB)—employee behaviors that detract from the collective goals or well-being of an organization (Ones et al., 2018). Although cyberloafing can be restorative to individual mood and well-being (Lim & Chen, 2012), these behaviors are conducted "while an employee is supposed to be performing job tasks" (Pindek et al., 2018, p. 147). Due to this conceptual alignment and the strong correlation between CWB and cyberloafing (ρ = .38; Mercado et al., 2017), our investigation was enriched by the robust nomological network of CWB.

A Person-Situation Cyberloafing Framework. To fully comprehend how behaviors manifest, it is imperative to take a wholistic approach (e.g., Lewin, 1939). Individuals do not experience the objective world around them; rather, their experiences are filtered through a variety of attitudes, beliefs, and past experiences, among myriad other factors. This produces two consequences relevant to cyberloafing. First, holding the person constant, different situations and contexts will likely yield different behavioral responses (Judge & Zapata, 2015). Second, holding the situation constant, people's unique constellation of traits and developmental trajectories will cause differences in experiences and perceptions that will likely yield different behavioral responses (Mumford & Owens, 1987; Spector & Fox, 2010). Considering that "behavior is derived from the totality of coexisting and interdependent forces that impinge on a person" (Burnes & Cooke, 2013, p. 410), any investigation into one or two behavioral antecedents will be necessarily deficient. Cyberloafing must therefore be understood by the collective effects of both person-centric and situation-centric constructs.

In the CWB domain, although both personological and situational constructs are important, their relative contribution is not equal. Lending support to self-control theories of general counterproductivity (Gottfredson & Hirschi, 1990), Marcus and Schuler (2004) found a stronger collective effect of personological predictors than for situational constructs. Although cyberloafing relates to CWB, evidence suggests that these two constructs exhibit differential patterns of relationships with personological and situational constructs (e.g., Pindek et al., 2018). Most prominently, the Big Five personality dimensions exhibit drastically weaker validities for predicting cyberloafing (ρs ranged from .00 to -.16; Mercado et al., 2017) than for overall CWB (ρs ranged from .02 to -.46; Berry et al., 2007). Conversely, contextual factors, such as organizational and social factors (e.g., Askew et al., 2014; Pee et al., 2008) tend to play comparatively larger roles in predicting cyberloafing than for CWB (Pindek et al., 2018). Considering personological and situational factors are inherently tied to different organizational interventions (e.g., personnel selection vs. conflict management), there is a great need to further our understanding of cyberloafing precursors. Understanding which precursors most directly and impactfully influence cyberloafing can guide researchers and practitioners towards fruitful directions and underlies the motivation for our first research question (RQ1): What is the comparative impact of personological and situational/contextual variables on cyberloafing? Because organizational interventions tend to focus on one or two focal variable domains—as opposed to general classes of variables—a logical follow-up question was also of interest (RQ2): Which are the most important individual variables for predicting cyberloafing?

Predictor Selection. To empirically assess potentially important cyberloafing correlates, we first had to identify a plausible set of variables. These variables were rationally selected based on the following criteria: each variable must (a) have a comparatively large relationship with cyberloafing or CWB more broadly, (b) be conceptually or theoretically linked to cyberloafing or CWB more broadly, and/or (c) be popular[1] correlates studied with greater frequency than alternatives. As a collective, the set of variables should generally represent both personological and situational variables and include a diverse set of variable domains to reduce the (conceptual and statistical) overlap between domains. Two comprehensive reviews influenced predictor selection: a quantitative review of 39 cyberloafing correlates (Mercado et al., 2017) and a synthesis of 89 published and unpublished meta-analyses of the broader CWB domain (Ones et al., 2018). From here, variables that are not applicable to guided interventions were deemed inappropriate for our study and thusly dropped from consideration. As a result, some previously identified cyberloafing correlates with sizable effects were excluded due to a lack of direct interventionist guidance. For example, cyberloafing norms, intentions, and neutralization are surely related to cyberloafing behaviors (Ones et al., 2018) but have weak

1 Some may regard popularity as a tenuous criterion for inclusion. Nonetheless, variable importance metrics for popular constructs are informative because new directions for future research are suggested if popular constructs prove unimportant. Moreover, because some popular domains (e.g., justice and satisfaction) are already assessed in many organizational settings, commonly applied interventions might reduce cyberloafing.

associations with directly actionable interventions without the inclusion of further information. Behavioral intentions relate to behaviors but do not convey *why* the intention arose in the first place. Similarly with neutralization, feeling entitled to cyberloaf does not elucidate the context or decision making process giving rise to that entitlement. Some domains, such as with personality traits, have multiple constructs that were potentially relevant but, due to parsimony, the most relevant construct was selected (e.g., as described below, Big Five personality traits were selected over self-control). Most notably, demographic constructs were omitted due to their generally low effect sizes and their questionable legal defensibility in organizational initiatives. The final set of cyberloafing antecedents, along with their definitions, construct domains, and rationale for inclusion, is presented in Table 1. In the following sections we first describe person-centric constructs followed by situation-centric constructs.

Personological Constructs. Personological constructs herein refers to attributes describing the basic tendencies (e.g., traits) and characteristic adaptations (i.e., adapting personal characteristics to better operate in one's environment; DeYoung, 2015; Motowildo et al., 1997) of individuals. Although these variables may interact with specific contexts, their effects cannot be attributed to or duplicated by contextual characteristics. Many personological constructs are potentially related to workplace behaviors; however, theories of job performance more broadly, and counterproductive work behaviors more specifically, have provided ample insights into key variable domains associated with on-the-job behaviors, such as cyberloafing (Campbell et al., 1993; Motowildo et al., 1997). Therefore, we have identified four potentially potent personological predictors of the cyberloafing domain: job attitudes, boredom, personality, and cognitive ability. In what follows, each domain is introduced and briefly related to cyberloafing.

Job attitudes, as characteristic adaptations (e.g., DeYoung, 2015) arising from a person's disposition (Judge et al., 2002; Staw et al., 1986), relate to individual motivation at work by directing efforts toward desirable objectives while eschewing negative objectives. Specifically, withdrawal behaviors are well-established outcomes of negative attitudes (Carpenter & Berry, 2017; Rosse & Hulin, 1985; Weiss & Cropanzano, 1996). By far, the most commonly studied job attitude has been job satisfaction, referring to general feelings of satisfaction about one's work (e.g., satisfaction with the work environment, pay, peers; Dalal, 2012). Given its predictive utility for positive (Riketta, 2008) and negative (Tett & Meyer, 1993) organizational criteria, it is unsurprising that job satisfaction is the most frequently studied non-demographic cyberloafing antecedent.

Emotions, such as employee boredom, demonstrate similar potential for redirecting employee motivation. Boredom refers to a "negative (i.e., unpleasant, dissatisfying) and often deactivating (i.e., low arousal) activity-related emotion, implying that the activity (e.g., the work task) acquires negative intrinsic value" (van Hooff & van Hooft, 2014, p. 349). Rather than being motivated to perform their job, bored employees are motivated to reduce their boredom, often through counterproductive acts (Bruursema et al., 2011) or loafing behaviors (e.g., working slowly, taking an extended lunch; van Hooff & van Hooft, 2014). A recent study (Pindek et al., 2018) explored boredom as a mediator between low workload and cyberloafing behaviors, corroborating recent meta-analytic evidence of a strong bivariate relationship with cyberloafing (Mercado et al., 2017).

In understanding and explaining job performance, individual differences in personality are some of the most commonly studied antecedents, and for good reason (Schmidt & Hunter, 1998). Cybernetic theories of personality (DeYoung, 2015, p. 33) suggest that personality manifests as "characteristic patterns of behavior," meaning that personality characteristics are markers indicating which individuals have a greater propensity for certain behaviors, like cyberloafing. Indeed, meta-analyses have uncovered a set of personality traits that routinely predict patterns of undesirable workplace behaviors. Specifically, the core traits of conscientiousness, agreeableness, and emotional stability correlate with cyberloafing (ρs range from -.11 to -.16; Mercado et al., 2017) and related phenomena (e.g., Berry et al., 2007). In the personality domain, the shared variation among these three factors represent an important personality construct (i.e., a higher-order metatrait) that is commonly referred to as stability (Digman, 1997; Stanek & Ones, 2018). Stability—also labelled Factor Alpha or socialization—reflects a person's propensity for self-regulating behaviors, maintaining self-composure, and behaving in a socially acceptable manner (Stanek & Ones, 2018). Supporting the use of the stability metatrait for applied research, cyberloafing researchers and practitioners rarely utilize individual personality traits in isolation (e.g., Brock et al., 2013). As we seek to understand the relative importance of personality more broadly, bandwidth-fidelity arguments support that investigating personality at the aggregated metatrait level will provide meaningful and interpretable results to fuel future recommendations regarding intervention strategies.

Despite its eminence in the job performance literature, the influence of cognitive ability on cyberloafing has yet to be explored. Similarly, the somewhat related CWB literature has only sparsely examined this important construct. Some studies have uncovered marked (negative) relationships between cognitive ability and objective measures of CWB (e.g., Dilchert et al., 2007), whereas meta-analytic estimates including self-reported criterion measures show a near-zero average relationship (albeit with sizable variability) between cognitive ability and CWB (Gonzalez-Mulé et al., 2014). Combining the established positive relationship between cognitive ability and task performance (Schmidt & Hunter, 1998) with these null to negative associations with counterproductive behaviors reinforces the benefits of hiring highly intelligent employees. However, as previous scholars (e.g., Pindek et al., 2018) have shown, some predictors demonstrate substantively different relationships with cyberloafing than with general CWB.

Because understimulated employees may cope via extra-task behaviors (Pindek et al., 2018; van Hooff & van Hooft,

Table 1. Descriptions and inclusion rationales for cyberloafing antecedents

Construct	Definition	Construct domain	Rationale for inclusion
Personological Predictors			
Job satisfaction	General feelings of satisfaction about one's work[h]	Attitude	• Progression-of-withdrawal theory[o] • Affective events theory[v] • Empirical relationships with related criteria[h, m, t] • Popular cyberloafing predictor[k]
Work-related boredom	Negative, deactivating emotional response to a negatively viewed task[u]	Emotion	• Affective events theory[v] • Empirical relationships with CWB and cyberloafing[l, u] • Strong cyberloafing predictor[k]
Stability metatrait	Propensity for self-regulating behaviors, maintaining self-composure, and behaving in a socially acceptable manner[s]	Personality	• Cybernetic theory of personality[i] • Empirical relationships with CWB and cyberloafing[b, k]
Logical reasoning	Deducing the correctness of a conclusion	Cognitive ability	• Relationships with understimulation[q] • Empirical relationships with CWB[j]
Situational Predictors			
Organizational justice	Perceptions of fairness within an organization	Justice	• Stressor-emotion theory of counterproductivity[p] • Equity and social exchange theories[a, g] • Empirical relationships with CWB[e, f] • Popular cyberloafing predictor[k]
Employee workload	One's perceived volume of work[r]	Demands	• Stressor-emotion theory of counterproductivity[q] • Empirical relationships with withdrawal[d] and cyberloafing[l]
Interpersonal conflict at work	Frequency and severity of harassment from colleagues[r]	Stressors	• Stressor-emotion theory of counterproductivity[p] • Empirical relationships with CWB[c] and withdrawal[n]

Note. [a]Adams, 1965; [b]Berry et al., 2007; [c]Bowling & Beehr, 2006; [d]Bowling et al., 2015; [e]Cohen-Charash & Spector, 2001; [f]Colquitt et al., 2013; [g]Cropanzano & Mitchell, 2005; [h]Dalal, 2012; [i]DeYoung, 2015; [j]Dilchert et al., 2007; [k]Mercado et al., 2017; [l]Pindek et al., 2018; [m]Riketta, 2008; [n]Robinson et al., 2014; [o]Rosse & Hulin (1985); [p]Spector & Fox, 2005; [q]Spector & Fox, 2010; [r]Spector & Jex, 1998; [s]Stanek & Ones, 2018; [t]Tett & Meyer, 1993; [u]van Hooff & van Hooft, 2014; [v]Weiss & Cropanzano (1996)

2014), we questioned if the otherwise desirable characteristic of intelligence may also contribute to understimulation. Specifically, highly intelligent individuals are comparatively underchallenged and thusly understimulated (Spector & Fox, 2010). Furthermore, the established rationale for why highly intelligent employees might engage in fewer CWB—that they demonstrate greater long-term thinking and the necessary foresight to consider negative consequences (e.g., Lynam et al., 1993)—does not readily extend to cyberloafing. Cyberloafing behaviors are easily concealed and are sometimes normative within organizations (Cheng et al., 2018). Thus, consequences associated with cyberloafing may be less severe than for other CWB (e.g., theft, sabotage). Considering the more frequent understimulation of highly intelligent employees and the relative lack of consequences for cyberloafing, we include cog-

nitive ability as a potential (positive) driver of cyberloafing. Furthermore, provided that cognitive ability and boredom both putatively relate to understimulation, our multivariate study is well-suited to disentangling the relative merits of boredom versus cognitive ability in predicting cyberloafing.

Situational Constructs. Thus far, we have emphasized the role of personological constructs, such as boredom and personality, that influence how employees behave. However, employees do not exist in a vacuum; external factors, such as characteristics of the organizational context, also meaningfully impact employee behavior (e.g., Blanchard & Henle, 2008; Fox et al., 2001; Liberman et al., 2011). Many of these situational effects have been characterized as stressors and have therefore been integrated into the CWB domain via the stressor-emotion model of counterproductivity (Spector & Fox, 2005). The model and subsequent research posits that CWB, including cyberloafing, are often enacted as a coping mechanism to assuage emotional reactions to stressors (Fox et al., 2001; Pindek et al., 2018). For instance, understimulation (Spector & Fox, 2010) at work elicits negative reactions (Weinberg, 2016) and has been shown to give rise to CWB as a method to cope with the situation. Therefore, we explore the relative contribution of three commonly studied situational effects for predicting cyberloafing: organizational justice, employee workload, and interpersonal conflict.

Organizational justice—perceptions of fairness within an organization—is commonly explored as a cyberloafing antecedent and is moderately related to avoiding counterproductivity in general (e.g., Cohen-Charash & Spector, 2001; Colquitt et al., 2013). According to equity (Adams, 1965) and social exchange (Cropanzano & Mitchell, 2005) theories, employees inherently value justice, giving rise to behaviors that promote justice and/or to rectify injustice. Along this vein, an employee perceiving injustice "would be inclined to reinstate a sense of justice" (Lim, 2002, p. 687) by engaging in cyberloafing. Like job satisfaction, despite its popularity and strong theoretical foundations supporting a relationship with cyberloafing, justice typically demonstrates somewhat weak effects on cyberloafing (Mercado et al., 2017). These surprising findings might be informed by our multivariate approach.

Employee workload (i.e., one's perceived volume of work; Spector & Jex, 1998) is another organizational stressor that impedes performance (Bowling et al., 2015), as illustrated by meta-analytic findings of the modest relationship between workload and withdrawal (e.g., turnover intentions, absenteeism; Bowling et al., 2015). Relatedly, Pindek and colleagues (2018) recently explored employee workload as an antecedent to both cyberloafing and CWB. They reported a moderately strong relationship between workload and cyberloafing (r = -.27) despite virtually no relationship with CWB (r = -.02). Coupling these empirical findings with the stressor-emotion model highlight workload as a promising cyberloafing antecedent.

Interpersonal conflict at work (Spector & Jex, 1998) generally refers to the frequency and severity of experienced harassment at work (e.g., "how often do people yell at you?"). To our knowledge, no study has previously examined whether victims of workplace conflicts engage in more cyberloafing behaviors. Nevertheless, meta-analytic reviews of the related CWB domain suggest that victims of harassment and conflict are notably more likely to engage in counterproductivity (ρ = .37; Bowling & Beehr, 2006). The effects of conflict are far-reaching; like victims, bystanders witnessing workplace conflict also tend to manage their stressful experiences by engaging in negative coping behaviors, such as withdrawal or disengagement from work (Robinson et al., 2014). As an avoidant coping mechanism or a form of escapism (Pindek et al., 2018), cyberloafing would therefore be expected to serve as an attractive avenue for those exposed to conflict. Thus, we include interpersonal conflict at work in our study for two reasons: (a) to expand the cyberloafing nomological network, potentially uncovering an important cyberloafing antecedent, and (b) because conflict is an actionable variable that can be addressed via targeted interventions.

Purpose of this Study. This study builds on previous research by investigating the role of a diverse and potentially important set of cyberloafing antecedents using a multivariate framework (i.e., dominance analysis; Budescu, 1993). We acknowledge the potentially noteworthy intercorrelations among these variables (e.g., stability and job satisfaction); however, unlike traditional bivariate analyses, our multivariate approach using dominance analysis allows for unraveling these relationships by explicitly controlling for predictor intercorrelations. We hope that establishing the relative impact of personological and situational variables on cyberloafing (RQ1), as well as the most important predictors of cyberloafing (RQ2), will promote the use of empirically-founded guidance to aid employers in managing cyberloafing. Moreover, because two of the included constructs have not been previously explored in relation to cyberloafing, an additional contribution of this study is the expansion of the cyberloafing nomological network.

Methods

Samples and Procedure

Data were collected from three independent samples via voluntary, online surveys. To be deemed eligible, participants had to answer "yes" to at least one of the following two screening items: "Does your organization provide access to technology (phones, computers, other electronic devices)?" and "Do you use any personal technological device (a smartphone, tablet, or laptop) while at work?". Note that in our data collection efforts, not all samples were provided every test battery[2], such that discrepancies in the sample size for each variable interrelation are predominantly due to survey administration rather than incomplete participant responses.

Sample 1 consisted of 639 employed students from two urban universities who volunteered to gain course credit. The sample was 38.8% male and very diverse in terms of race and ethnicity (48.4% White/Caucasian, 38.7% Asian, 8.3% African American, 14.1% of Hispanic background; multiple responses were possible). Participants ranged in age from 18 to 52 (M_1 = 22.1, SD_1 = 4.8). The median num-

ber of hours worked per week was 23.5 (M_1 = 24.7, SD_1 = 10.2) and median job tenure was one year (M_1 = 1.7, SD_1 = 2.2). On average, participants had 4.8 years (SD_1 = 4.3) of total work experience. The majority (60.0%) were entry-level employees and 17.3% were intermediate-level employees without subordinates. Nearly one-quarter (22.7%) were managers, ranging from first-level supervisors to executives. Participants had access to a wide range of technology in the workplace, with a substantial proportion accessing an employer-provided computer (75.1%) or a personally owned smartphone (76.0%) while working.

To more broadly sample from the general workforce, we collected data from two additional samples. Samples 2 and 3 both consisted of full-time employees recruited via Amazon Mechanical Turk (MTurk; *N*s were 295 and 208, respectively). Samples 2 and 3 were 56.4% and 47.1% male, respectively, and predominantly Caucasian (75.9% and 82.2%). Participants ranged in age from 20 to 67 years (M_2 = 34.4, SD_2 = 9.4 and M_3 = 33.6, SD_3 = 10.0). Participants in both samples worked approximately 40 hours per week (M_2 = 41.6, SD_2 = 4.8 and M_3 = 42.0, SD_3 = 5.7); median work tenure was 3.8 and 3.5 years, respectively. Participants had substantial work experience (M_2 = 14.1, SD_2 = 8.9 and M_3 = 13.9, SD_3 = 10.1). Over 40% of each sample had managerial responsibility and fewer than 15% of each sample were entry-level employees. Participants had extensive access to technology in the workplace; nearly all (90.2% and 94.7%) accessed an employer-provided computer, and the vast majority (76.4% and 82.2%) accessed a personal smartphone while working.

When properly administered and evaluated, data drawn from MTurk and student populations can be as informative and valid as comparable data drawn from an organization (Cheung et al., 2017; Landers & Behrend, 2015; Walter et al., 2019). We carefully considered the appropriateness of each sample and cautiously designed the studies per leading guidelines. Specifically, student samples are appropriate for investigating cyberloafing as they tend to be range restricted in variables typically unrelated to cyberloafing (e.g., age and education; Mercado et al., 2017). Moreover, collecting data via MTurk added to the external validity of our results by (a) broadly sampling working individuals and (b) affording extra anonymity when evaluating potentially sensitive behaviors. Most important of all, the broad sampling of people, jobs, and organizations from employed students and MTurk participants helps maximize the generalizability of our results to working adults in the US. Beyond sampling choices meant to enhance external validity, we also followed recommendations to maximize internal validity when designing the data collection and screening procedures. For example, per Cheung and colleagues' (2017) guidelines, we (a) integrated attention checks, (b) implemented data screening procedures, and (c) used custom MTurk qualifications to reduce the effects of inattentiveness and repeated participation.

Measures

Job Satisfaction. Empirical evidence supports the validity and utility of single-item measures of job satisfaction, particularly when describing overall satisfaction—compared to its specific elements—is the main focus (Scarpello & Campbell, 1983; Wanous et al., 1997). We therefore measured job satisfaction across the three samples using the following item from Scarpello and Campbell (1983): "How satisfied are you with your job in general?" Responses were anchored on a five-point scale ranging from "very dissatisfied" to "very satisfied." To yield conservative meta-analytic corrections for relationships with job satisfaction, we used an internal consistency estimate of .84 (Dormann & Zapf, 2001) rather than the lower cross-scale estimate of .67 (Wanous et al., 1997).

Boredom. Similar to Pindek and colleagues (2018), we found Lee's (1986) Job Boredom Scale to be relevant yet contaminated by additional constructs (e.g., employee satisfaction, job characteristics). It therefore formed the basis for our focused, three-item measure of work-related boredom. Participants were asked to indicate their agreement with the following statements: "I often get bored with my work," "I find my job dull," and "I experience long periods of boredom at work." A five-point agreement scale was used and the average internal consistency reliability across the three samples was .92.

Stability. Personality was assessed using the Big Five Aspect Scale, a public domain personality measure that was constructed using items from the International Personality Item Pool (DeYoung et al., 2007). This measure yields scores for the Big Five factors of emotional stability, extraversion, openness, agreeableness, and conscientiousness, as well as their two respective aspects (measured by 10 items each). To measure stability (DeYoung, 2015; Digman, 1997), we created a composite between conscientiousness, agreeableness, and emotional stability. Composite validities (and reliabilities) were computed within each sample before meta-analyzing across studies. The average composite reliability across three samples was .92.

Cognitive Ability. In this study, we focused on assessing the specific fluid ability of logical reasoning. Several lines of evidence suggest that logical reasoning is a useful proxy for cognitive ability. In their taxonometric work, Stanek and Ones (2018) and McGrew (e.g., McGrew, 2009) report that general sequential reasoning is central to fluid ability. Kyllonen and Christal (1990) among others have demonstrated that nonsense syllogisms are core to fluid ability, which is itself isomorphic with general cognitive ability (Gustafsson, 1984). Although nonsense syllogisms are not a perfect proxy for cognitive ability, this assessment serves as a good and well-established representation of the broader domain. Therefore, we administered the nonsense syllogisms test from the Educational Testing Service Research Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976). Sub-

2 The Measures section below describes how many samples are included for each construct assessment.

jects are presented with nonsensical syllogisms and must evaluate whether each syllogism is true, false, or undetermined. This proprietary test consists of two separately timed sections; for the online version administered, item order was randomized within each page. While internal consistency estimates can be problematic for speeded tests, randomized item order helps counteract these problems. To estimate reliability, we computed separate Cronbach's alpha estimates for each of the two parts and computed the reliability of the composite. The averaged composite reliability across the two samples was .62.

Organizational Justice. We measured perceptions of organizational justice via Colquitt's (2001) 20-item measure, which consists of four subscales assessing distributive, procedural, interpersonal, and informational justice. The dimension subscales were composited to produce an overall organizational justice variable for two reasons. First, justice dimensions are often highly intercorrelated (Colquitt, 2001; Colquitt et al., 2013), which can introduce instability when estimating parameters. Second, and more relatedly, our study attempts to discern the relative importance of organizational justice overall. Therefore, composite validities and reliabilities were computed within a sample before meta-analyzing across samples. The average composite reliability across the two samples was .98.

Workload. We administered Spector and Jex's (1998) five-item Quantitative Workload Inventory (QWI) to assess the quantity of work employees are assigned. An example item is "How often do you have to do more work than you can do well?" The mean internal consistency reliability estimates across the two samples that completed this measure was .84.

Interpersonal Conflict. We administered Spector and Jex's (1998) Interpersonal Conflict at Work Scale (ICAWS). The ICAWS includes four items, such as "How often do other people yell at you at work?" to assess employees' experiences of interpersonal conflict. The mean internal consistency reliability estimates across both samples was .86.

Cyberloafing. We administered Mercado's (2017) seven-item cyberloafing scale, which is not restricted to specific occupational settings or technological media. Sample items include, "Send non-work related messages while you should be working" and "Browse non-work-related websites while you should be working." Evidence indicates that vague quantifiers (e.g., rarely, frequently; Wänke, 2002) are influenced by perceived norms and idiosyncratic interpretations. Consequently, instructions asked participants to indicate how frequently they engaged in each behavior using a seven-point, specific frequency scale with the anchors "never," "once a year," "several times a year," "once a month," "once a week," "once a day," and "several times a day."

Analyses

Three sets of analyses were conducted to address the focal questions in the present investigation (see the online supplement for all R code, output, and methodological details). First we aggregated the samples using meta-analytic techniques[3] to (a) reduce the detrimental effect of statistical biases (i.e., sampling error and unreliability), (b) improve desirable statistical properties (e.g., power; Cohn & Becker, 2003), and (c) theoretically assess construct-level relationships. An added benefit of this aggregation approach is the application of statistical indices (e.g., estimates of effect size heterogeneity) to further assess the appropriateness of combining samples. Before combining samples, a composite was created for stability and organizational justice within each sample. Then, samples were aggregated using a sample-size-weighted average. Averaged effect sizes were corrected for unreliability in the predictor and criterion variables based on an artifact distribution of sample reliabilities. Composite reliabilities were estimated to correct for unreliability in composite constructs. These steps yielded an aggregated correlation matrix representing the theoretical true score validities between each construct. See the Supplement for results of analyses conducted on uncorrected correlations.

Next, we compare the relative importance of the person and situation construct domains. To do so, two pairs of incremental validity analyses (i.e., hierarchical regression) were conducted. In one model, person variables were entered as baseline predictors and situation variables were added in the second step. In the other model, these two steps were reversed. Incremental validities were assessed via shrunken fit indices (i.e., ΔR^2) to control for the number of predictors in the model. The sample size was obtained by taking the harmonic mean of the bivariate relationships (Viswesvaran & Ones, 1995).

Lastly, to quantify the variable importance for all predictors, we conducted dominance analyses (Azen & Budescu, 2003; Budescu, 1993; Thomas et al., 2014). In short, dominance analysis quantifies the relative contribution of each predictor in explaining variance in the criterion (R^2). The relative contribution of a variable is measured by the amount of additional variance in the criterion explained by that variable (i.e., ΔR^2), relative to a baseline model. In dominance analysis, baseline models are created for all possible combinations of predictor sets—wherein sets range from a null model with no predictors to models including all but one predictor—before measuring the relative contribution of each variable.

Comparing the relative contribution of the included predictors can result in three different levels of dominance (for a more thorough description, see Azen & Budescu, 2003). The first (and most stringent) dominance criterion

3 Note that this is a primary study, drawing upon three samples, to investigate the cyberloafing domain. Whereas we use meta-analytic techniques to aggregate the three samples, our study should not be interpreted as a comprehensive meta-analysis on the subject. For another example of this use of meta-analysis, see Fleeson and Gallagher (2009).

is complete dominance. A variable is completely dominant if it provides the most additional variance across all possible models. The second dominance criterion is conditional dominance. Conditional dominance occurs if a variable contributes more variance, on average, when *conditioning* on the size of the model (i.e., the number of predictors examined in the base model, denoted by *k*). The third—and least stringent—dominance criterion is general dominance. A variable is generally dominant if it has the largest average conditional dominance metric across all model sizes. To illustrate these dominance criteria, we provide a simple example below.

Consider a simple dominance analysis example with three variables: boredom, stability, and justice. With three predictors, eight possible models (modeling each of the possible pairings of predictors) are examined. In a pairwise comparison of boredom and justice, there are two baseline models that will be tested. One model is a null model with no baseline predictors and the other model includes stability as a baseline predictor. If boredom is associated with a larger ΔR^2 value in both models, then boredom is completely dominant. If boredom is associated with a larger ΔR^2 value in the null model but not the baseline stability model, then boredom is conditionally dominant when the model size is zero (i.e., no other predictors in the baseline model). Lastly, a variable will be generally dominant if it is associated with the larger average ΔR^2 value across the two conditioned model sizes (i.e., when $k = 0$ and $k = 1$).

Results

The corrected correlation matrix (and aggregated reliability indices) summarizing the three samples is reported in Table 2. Boredom (ρ = .27), logical reasoning (ρ = .22), and conflict (ρ = .16) were moderately and positively related to cyberloafing, whereas stability (ρ = -.18) exhibited a moderate negative effect. Organizational justice (ρ = -.04), job satisfaction (ρ = -.04), and workload (ρ = -.08) had weak relations with cyberloafing. Indexing the degree of effect size heterogeneity, the *SD*ρ[4] values displayed in Table 2 are all of a trivial magnitude with a modal value of zero. Thus, there does not appear to be systematic differences across our three samples, bolstering the cross-sample generalizability of our results.

Whereas effects appear to hold across our samples, thanks to a reviewer comment, we also explored whether occupational groups differed with respect to the included variables (see the online supplement for tables and figures). Our participants' jobs were categorized into five occupational groups (Oswald et al., 1999) based on the amount of preparation needed to enter an occupation. There appears to be little variation across occupational groups for most of the included variables. Although cyberloafing varies somewhat across groups, there is clearly more variation within groups than across groups. As expected, personality systematically increases—albeit with small absolute differences—with occupational preparation, a consequence of selection into occupations and organizations, training, and advancement opportunities. Boredom, however, shows the reverse pattern with less boredom as occupational preparation increases. The remaining variables were generally unrelated to occupational differences. In general, the magnitude of the differences across groups is small and would not appreciably attenuate effects in the focal analyses.

Answering RQ1, Table 3 displays the general comparison of person versus situation constructs in relation to cyberloafing. In the top half of the table, constructs tapping into the organizational context (i.e., justice, workload, and workplace conflict) added relatively little to the cyberloafing criterion (shrunken $\Delta R^2 = .03$). Alternatively, the bottom half demonstrated that adding person-centric constructs yielded a comparatively larger increase in explained cyberloafing variance (shrunken $\Delta R^2 = .13$). In the cyberloafing domain, results suggest that person-centric constructs are more influential than situational constructs. Collectively, this constellation of antecedents explained a sizable amount of variability in the cyberloafing criterion ($R = .42$, shrunken $R^2 = .16$).

Our second research question (RQ2) asked which are the most important variables for predicting cyberloafing. To answer RQ2, we quantified variable importance for the individual constructs, conducting dominance analyses characterized by 128 multiple regressions (summarized in Table 4). For brevity, only the conditional and general dominance findings are reported in Table 4 (see the Supplement for the results of all 128 comparisons). Although not discernible from Table 4, boredom was close to achieving complete dominance (i.e., explaining more additional variance in all analyses). Boredom dominated all variables except for logical reasoning, which it dominated in 28 of their 32 (87.5%) pairwise comparisons. Nevertheless, Table 4 illustrates that boredom is both conditionally and generally dominant over all other variables. Recall that the conditional dominance criterion is met when a variable explains more variance on average than other variables after conditioning on the number of predictors in the baseline model (e.g., $k = 2$ corresponds to all combinations of two predictors). Moreover, the general dominance criterion is met when a variable is associated with a larger average conditional dominance metric. In other words, our results demonstrate that, no matter the size of the regression model, boredom, on average, explains more variance in cyberloafing than the alternative correlates.

4 In this study, individual *SD*ρ values should not be interpreted as reflecting estimated population variability in the effect size. Meta-analysis was herein used to combine samples, not to estimate population parameters. Moreover, variability estimates based on two or three data points are both unstable and imprecise. That being said, the *pattern* of the *SD*ρ values provides tentative evidence that the distinct samples do not appreciably differ from each other in their effect sizes.

Table 2. Meta-Analytic Intercorrelation Table

	Job satisfaction	Boredom	Stability	Logical reasoning	Justice	Workload	Conflict	Cyberloafing
Job satisfaction	*.84*							
Boredom	-.50 (.17; 769)	*.92*						
Stability	.30 (.07; 758)	-.41 (.06; 759)	*.93*					
Logical reasoning	.02 (.10; 345)	-.01 (.00; 345)	-.01 (.00; 481)	*.62*				
Justice	.65 (.00; 351)	-.50 (.00; 351)	.36 (.00; 340)	.05 (.00; 343)	*.98*			
Workload	-.18 (.00; 351)	.05 (.00; 351)	.10 (.05; 340)	-.06 (.07; 343)	.00 (.00; 351)	*.84*		
Conflict	-.43 (.00; 351)	.32 (.00; 351)	-.38 (.00; 340)	-.14 (.00; 343)	-.44 (.00; 351)	.21 (.00; 351)	*.86*	
Cyberloafing	-.04 (.00; 766)	.27 (.03; 767)	-.18 (.00; 1,121)	.22 (.02; 482)	-.04 (.00; 348)	-.08 (.00; 348)	.16 (.00; 348)	*.87*

Note. Correlation coefficients are corrected for attenuation due to unreliability on both predictor and criterion. Values in the parentheses indicate SD_ρ and total sample size, respectively. Values on the diagonal are the averaged internal consistency estimates for each multiple-item scale across samples. The reliability estimate for job satisfaction was obtained from Dormann and Zapf (2001). Justice = organizational justice. Conflict = interpersonal conflict.

Table 3. Incremental Validity of Person Versus Situation Constructs in Predicting Cyberloafing

Step	R	R^2	ΔR^2
Step 1: Person	.37	.13	
Step 2: Situation	.42	.16	.03
Step 1: Situation	.20	.03	
Step 2: Person	.42	.16	.13

Note. Shrunken $R2$ and $\Delta R2$ values are reported based on a harmonic mean sample size (N = 404.5).

Also shown in Table 4, logical reasoning is the second most dominant variable—as evidenced from the conditional and general dominance results. Furthermore, our results conclusively illustrate that logical reasoning completely dominates all other variables (except for boredom). The dominance results for the third most dominant variable, interpersonal conflict, are less conclusive. Conflict only meets the criterion of general dominance over the remaining variables. In two sets of conditional dominance analyses (i.e., k = 0 and 1), conflict is surpassed by stability. Whereas conflict generally dominates stability, these findings highlight the need to examine variable importance in a multivariate framework. Specifically, stability has a larger absolute bivariate correlation (ρ = -.18) with cyberloafing than does interpersonal conflict (ρ = .16). However, conflict, on average, is more generally important (average additional variance explained = 2.44%) than stability (average additional variance explained = 1.47%).

It is apparent from Table 4 that boredom, logical reasoning, and interpersonal conflict at work are the three most important cyberloafing antecedents. However, the rank-ordering of the remaining four variables is less clear. For instance, justice appears to act as a suppressor variable in the cyberloafing domain. Namely, justice becomes a stronger predictor of cyberloafing as the model size increases. Thus, the relative importance of justice largely depends on the size of the model. Alternatively, the importance of stability follows the opposite trend as justice. Namely, as more predictors are examined, stability quickly becomes a less important cyberloafing antecedent. Nevertheless, the exact rank-order of workload, justice, satisfaction, and stability is of a lesser consequence for practical applications as their average contributions to explaining cyberloafing behaviors are comparatively low in magnitude (i.e., average variance explained between .47% and 1.47%).

***Post-Hoc* Analyses.** The results of the dominance analysis substantiated the importance of both logical reasoning and interpersonal conflict at work, the two variables that had not previously been investigated in relation to cyberloafing. Therefore, we also conducted exploratory post-hoc analyses to determine the incremental validity of these two variables beyond the other established predictors in our variable set. The baseline model with previously established cyberloafing antecedents (i.e., job satisfaction, boredom, workload, justice, and stability) fit the data well (R = .32) but was notably incremented by adding the novel predictors of conflict and logical reasoning (R = .42, shrunken ΔR^2 = .07). Conflict and logical reasoning are clearly impactful antecedents that warrant follow-up inquiries vis-à-vis cyberloafing.

Discussion

The central goal of this paper was in uniting disparate construct domains to identify the most important, proximal constructs—emphasizing those with actionable and practical relevance—for explaining variance in employee cyberloafing. In other words, we sought to empirically guide attempts to reduce cyberloafing by identifying potential cyberloafing antecedents particularly amenable to interventions. To encompass the employee life-space (Burnes & Cooke, 2013; Lewin, 1939), representative constructs were drawn from both personological and situational/contextual domains. Our results suggest that, of these two general domains, person-centric constructs have the greatest association with cyberloafing. These results are largely congruent with comparable findings from the CWB domain (Marcus & Schuler, 2004). On a more granular level, from seven diverse predictors across three samples, boredom, logical reasoning, and interpersonal conflict at work arose as the three most dominant cyberloafing predictors. Other scholars (e.g., Pindek et al., 2018) have previously identified boredom as an influential cyberloafing antecedent, but our study extends previous work in this domain by explicitly comparing the utility of boredom to several viable alternatives. Moreover, logical reasoning and experienced conflict are noteworthy as the second and third (respectively) most dominant constructs. Both cognitive ability and conflict are underexamined vis-à-vis cyberloafing, yet they are markedly more dominant than some of the more commonly studied predictors (e.g., justice, job satisfaction, personality), further cementing that "popularity has never been a scientific criterion of veracity" (Block, 2010, p. 5).

Expanding the Nomological Network of Cyberloafing

In our effort to identify the most important cyberloafing antecedents, we identified a set of diverse and potentially potent correlates. That list contained two variables that, to the best of our knowledge, have not been previously examined in relation to cyberloafing. Specifically, we extend the nascent nomological network of cyberloafing to include logical reasoning (i.e., a subdimension of cognitive ability) and workplace conflict, which were both relatively strong cyberloafing covariates. Whereas our study has entered logical reasoning and conflict into the scientific corpus of cyberloafing, our results do not shed light on the underlying causal mechanisms driving these relationships. Nevertheless, we can offer a tentative, post-hoc rationale to explain these linkages. Namely, employees tend to cyberloaf when understimulated at work (Spector & Fox, 2010) and when exposed to interpersonal conflict. If empirically substantiated, these hypothesized mechanisms would lend support to claims that cyberloafing behaviors serve as a coping mechanism for undesirable situations at work (Pindek et al., 2018). Beyond future empirical research needed to

Table 4. Conditional and General Dominance Analysis Results

		Job satisfaction		Boredom		Stability		Logical reasoning		Justice		Workload		Conflict	
	Model Size	% VE	Rank	% VE	Rank	% VE	Rank	% VE	Rank	% VE	Rank	% VE	Rank	% VE	Rank
Conditional Dominance	*k* = 0	.20	6.5	7.40	1	3.30	3	4.70	2	.20	6.5	.60	5	2.60	4
	k = 1	.32	6	7.05	1	2.47	3	4.84	2	.31	7	.69	5	2.33	4
	k = 2	.45	7	6.77	1	1.82	4	4.93	2	.53	6	.71	5	2.18	3
	k = 3	.58	7	6.62	1	1.28	4	4.98	2	.78	5	.73	6	2.20	3
	k = 4	.65	7	6.56	1	.84	5	5.04	2	1.00	4	.75	6	2.34	3
	k = 5	.62	6	6.56	1	.45	7	5.11	2	1.13	4	.79	5	2.57	3
	k = 6	.47	6	6.60	1	.14	7	5.20	2	1.17	4	.84	5	2.85	3
General Dominance	**Average:**	**.47**	**7**	**6.79**	**1**	**1.47**	**4**	**4.97**	**2**	**.73**	**5**	**.73**	**6**	**2.44**	**3**

Note. Conditional dominance results demonstrate, at each level of model size *k*, what proportion of variance is explained by each variable and its relative rank of importance. General dominance results demonstrate, on average, the proportion of variance explained by and rank of each variable. % VE = average proportion of additional variance explained (i.e., ΔR^2) by that variable conditioned on the model size.

examine these mechanisms, additional theoretical development is needed to better integrate the currently disjointed literatures of cognitive ability, conflict, and cyberloafing.

Implications for Research and Practice

As cyberloafing is a large contributor to wasted time at work (e.g., Kim & Christensen, 2017), many practitioners seek strategies to inoculate their organization against the downsides of cyberloafing (Conner, 2015). Despite the budding literature examining cyberloafing antecedents, comparatively few studies have bridged the gap between cyberloafing antecedents and cyberloafing interventions. Thus, we hope the results of our variable importance analyses and the extended cyberloafing nomological network will inform research on cyberloafing interventions. In theory, successful interventions should target important cyberloafing precursors and unsuccessful interventions likely target less important antecedents. Related to this latter point, Khansa and colleagues (2018) examined a justice-based cyberloafing intervention and found marginal effects on cyberloafing intentions (i.e., not actual behaviors). A weak effect for a justice-based intervention logically follows from our finding that justice is a (comparatively) unimportant cyberloafing antecedent. Instead of emphasizing less important variables, future attempts to curtail cyberloafing should instead emphasize boredom, cognitive ability, interpersonal conflict, or some combination thereof. Recognizing that interventions vary greatly (e.g., scope, theoretical foundations), we offer two potential intervention strategies based on our results that potentially warrant further investigations.

First, the intersection of logical reasoning, boredom, and cyberloafing supports understimulation (Spector & Fox, 2010) as being greatly associated with technologically-mediated idling at work. Intelligence may serve as a proxy for overqualification (Cheng et al., 2018; Maltarich et al., 2010, 2011), indicating that intelligent employees are insufficiently challenged and seek stimulation elsewhere via cyberloafing. Furthermore, others have previously demonstrated that bored employees are more likely to exhibit counterproductive behaviors, such as cyberloafing, as a result of their boredom (Mercado et al., 2017; Pindek et al., 2018; van Hooff & van Hooft, 2014). Therefore, researchers and practitioners should examine job enrichment interventions, such as job crafting, to combat cyberloafing by ensuring employees are sufficiently stimulated in their work.

Second, our results suggest that cyberloafing might be mitigated by managing workplace conflicts (Tjosvold et al., 2014). This finding parallels recent work suggesting that employees exposed to aggressive acts are more likely to cyberloaf (Andel et al., 2019). Taken together, these results highlight workplace conflict management as a promising domain for future cyberloafing interventions. Recognizing that such interventions range from individually-based to organization-wide, strategies should be tailored to the specific nature of the workplace conflict (Rahim & Bonoma, 1979). To facilitate strategic investments, a first step will likely involve data gathering to learn about the nature (e.g., prevalence, perpetrator, severity) of the conflict. For example, if conflict primarily originates from a few toxic workers (e.g., an abusive supervisor), behavioral interventions (e.g., training; Campbell et al., 2018) may prove beneficial. Alternatively, if conflict is endemic to the organization more broadly, organization-wide interventions or improved employee screening procedures (Fine, 2012; Ones et al., 1993) may be required to either fix the toxic climate or to hire less toxic employees.

Study Limitations and Future Directions

Dominance analysis (Budescu, 1993) is designed to quantify the relative importance of variables vis-à-vis some criterion and, as such, is well-suited for establishing the most important *proximal* predictors of cyberloafing. However, if a variable has a *distal* (e.g., causally mediated) effect, dominance analysis is ill-equipped to detect its importance in theoretical models. Future research into the causal mechanisms of cyberloafing should not interpret our results to mean that certain variables are holistically unimportant. Rather, variables of lesser importance may indeed serve as meaningful *indirect* determinants of cyberloafing (Campbell et al., 1993). To illustrate this, consider employee workload. We found one's workload to have (comparatively) low importance, but Pindek and colleagues (2018) found support for a structural model wherein boredom fully mediates the workload-cyberloafing relationship.

We explicitly designed our study to have generalizable results by collecting multiple samples and administering broadly applicable scales, yet future studies may extend our findings by taking a narrower focus. It may not be the case that all cyberloafing behaviors are equally mitigated by the same strategies. Studying granular behaviors (e.g., social media use versus video game play) may return a different pattern of variable importance values. Hypothetically, perhaps sending non-work-related messages (e.g., scheduling a dental exam) may not be a behavior amenable to interventions, browsing non-work-related websites (e.g., reading the news) may be a reactionary withdrawal (escapism) behavior in response to experienced conflict, and playing computer games may provide necessary stimulation to bored employees. If specific behaviors have distinct antecedents, granular investigations would improve the intervention capabilities of practitioners by empirically guiding tailored intervention strategies.

Our inclusion of two samples of employees from across the U.S. also strengthens the generalizability of our results. Most notably, drawing subjects from a single organization would appreciably restrict the range of organizational stressor variables, downwardly biasing their importance. Nevertheless, similar investigations into specific occupations or industries may produce results with different practical applications than those found herein. In our supplemental materials, we provide a breakdown of the means for each included variable across different occupational groups based on O*NET's categorization schema. There is tentative evidence to suggest that cyberloafing differs across occupational groups; although more variance is exhibited within groups, such group differences warrant further investigation. For instance, Maltarich et al (2010) found that the impact of cognitive ability on withdrawal (i.e., volun-

tary turnover) varied as a function of the cognitive demands of one's occupations. It is possible that (a) cyberloafing may manifest differently across occupations (e.g., by differential opportunities to engage) and (b) the importance of variables for understanding cyberloafing may differ across occupations (e.g., conflict may be more important in jobs requiring frequent interpersonal interactions).

Lastly, our study relies on self-reported, cross-sectional responses. When anonymity is guaranteed, self-reports are preferred for behaviors that are socially undesirable, difficult to observe, and easily hidden (Berry et al., 2012), all of which describe cyberloafing. Still, one problem with single-source data is the introduction of common method variance (Podsakoff et al., 2003), artificially inflating predictor intercorrelations. However, common method variance is more problematic in bivariate analyses than in dominance analyses, and its effect diminishes as more variables are added to the model, such as in the present study. Nevertheless, because cyberloafing occurs entirely via technology, it represents a prime opportunity for future scholars to use objective data collection methods (e.g., Black et al., 2013), such as electronic monitoring. Finally, our recommendations for potential intervention strategies are based on empirical findings from cross-sectional data. The potential interventions identified in our study necessitate more rigorous time-lagged and experimental testing to assess their viability in the long-term reduction of cyberloafing.

Conclusion

This study determined the relative contribution of seven diverse variables for the prediction of cyberloafing. Employee boredom, logical reasoning, and interpersonal conflict surfaced as the three most important cyberloafing correlates. Each of these three variables uniquely contributes to understanding cyberloafing above and beyond the variance explained by the remaining two. Practitioners trying to curb excessive cyberloafing can use our findings to guide the creation of tailored interventions for their organization. Specifically, two potentially fruitful intervention strategies for reducing cyberloafing behaviors are (a) job enrichment initiatives to mitigate understimulation at work and (b) training programs to stifle conflict in the workplace. These findings not only guide the strategic reduction of cyberloafing but also extend its nomological network to include previously unexamined, influential antecedents.

Contributions

Both authors contributed to conception and design, analysis and interpretation of data, and drafting and revising the article. The second author collected the primary data. Both authors approved the submitted version for publication.

Competing interests

We have no interests that would interfere with the integrity of this manuscript.

Funding

The first author was partially supported by the Auke Tellegen Fellowship in Applied Personality Assessment. This manuscript draws on data from the second author's dissertation. Those data collections were made possible by financial support from The Graduate Center Doctoral Student Research Grant (Cycles 08 & 10).

Data Accessibility Statement

All data and codes used to conduct these analyses are included in the online Supplement.

Submitted: June 15, 2021 PST, Accepted: September 14, 2022 PST

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