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SHORT COMMUNICATION

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# What are the odds of burnt-out risk and leaving the job? Turnover intent consequences of worker burnout using a two sample New Zealand study

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## Abstract

Job burnout is a pressing issue for organizations, and this study explores the new Burnout Assessment Tool (BAT), which provides a robust calculation of burnt-out risk. Next, the odds of high turnover intentions from burnt-out risk are calculated using two samples: (1) $N = 709$ employees and (2) $N = 313$ managers. Analysis shows the odds of burnt-out risk are higher for managers (17%) than employees (8%). High burnt-out risk in employees shows a 47% likelihood of high turnover intent versus 13% for employees with nonburnt-out risk. High burnt-out risk in managers shows a 51% likelihood of high turnover intent versus 12% for managers with nonburnt-out risk. Furthermore, moderating effects of supervisor organizational embodiment were found to interact with burnt-out risk for employees only, showing the highest turnover intent when embodiment is high, reflecting the potential backlash against the organization.

KEYWORDS

burnout assessment tool, burnt-out risk, managers, New Zealand, odds ratio, turnover intentions

## Practitioner Points

- Burnout is a critical factor in turnover intentions, but the most popular measure has been widely critiqued.
- This study uses the Burnout Assessment Tool (BAT), which more accurately captures employee burnout.
- It is the only burnout measure to provide a high burnt-out risk calculation.
- Finding's show burnt-out risk is higher for managers than employees.
- High burnt-out risk is critical to high turnover intent, even after controlling for many common factors.
- Organizational implications highlight the importance of using BAT to test for burnout risk, especially among managers.

## 1 | INTRODUCTION

Employee turnover is a perennial issue for Human Resource (HR) Management, including high costs from turnover intentions (see Bret Becton et al., 2009; Tillman et al., 2018), and meta-analytic links to firm performance (Park & Shaw, 2013). Li et al. (2016) contend the focus on turnover is moving away from traditional models, "emphasizing other determinants of turnover (e.g., shocks, family pressures, or duties) besides job attitudes" (p. 1437). Job burnout is an appropriate factor for predicting turnover intent enjoying meta-analytic support (Alarcon, 2011; Lee & Ashforth, 1996; Swider & Zimmerman, 2010). However, recent critiques show that the Maslach Burnout Inventory (MBI)—the most popular burnout construct (Schaufeli et al., 2020a)—has many issues. This includes issues around the MBI failing to mirror current understanding around burnout via its three dimensions.

This plays a role in the broader critique of the MBI (see Haar, 2021; Schaufeli et al., 2019, 2020a, 2020b; Van Heule et al., 2012). A new construct—the *Burnout Assessment Tool* or BAT (Schaufeli et al., 2019, 2020a, 2020b) offers a more robust approach to understand the links between burnout and turnover intentions. Especially because the BAT enables a *burnt-out* risk rate calculation (see Haar, 2021). The Conservation of Resources (COR) theory (Hobfoll, 2001) is used to understand why burnt-out risk represents a depleted state that ultimately drives turnover intentions.

## 2 | THE PRESENT STUDY

The purpose of the present study is to critique the MBI, and using the BAT with COR theory, to understand the role of burnout in understand employee turnover intentions. Recently, the MBI has been critiqued (Schaufeli et al., 2020a, 2020b) including what it does and does not measure. Concerns include the factor structure of the MBI (see Van Heule et al., 2012). Specifically, the professional efficacy dimension behaves differently (opposite) to the other two dimensions (Schaufeli et al., 2020b), creating issues around the overall construct. Furthermore, there are theoretical concerns around the MBI (Schaufeli et al., 2020b), and missing burnout dimensions such as reduced cognitive functioning (Deligkaris et al., 2014). Finally, the MBI does not enable a single burnout score to be calculated (and is discouraged, see Maslach et al., 2017). Ultimately, Schaufeli et al. (2020b) consider the MBI a burnout investigative tool and not a diagnostic tool, whereas the BAT acts as "a diagnostic tool for assessing burnt-out employees" (Haar, 2021; p. 2) and is used here to calculate odds for turnover intent. This suggests that BAT is a superior way than the MBI to measure burnout. The BAT has four dimensions: (1) exhaustion; (2) emotional impairment; (3) cognitive impairment; and (4) mental distance. Schaufeli et al. (2019) define them as follows.

> "(1) exhaustion, which refers to a severe loss of energy that results in feelings of both physical (tiredness, feeling weak) and mental (feeling drained and worn-out) exhaustion; (2) emotional impairment, which manifests itself in intense emotional reactions and feeling overwhelmed by one's emotions; (3) cognitive impairment, which is cued by memory problems, attention and concentration deficits and poor cognitive performance; (4) mental distance, which signals the degree of being psychologically distancing from the work and by a strong reluctance or aversion toward it" (p. 27).

Unlike the MBI, the BAT has strong empirical evidence of a higher-order construct (see Haar, 2021; Hadzibajramović et al., 2020; Sakakibara et al., 2020; Schaufeli et al., 2020a, 2020b). From this construct, employees with the most severe burnout score are referred to as being burnt-out (Haar, 2021) or having high burnt-out risk.

COR explains why some individuals experience the stressor-stress relationship differently, with those being less stressed having greater resources to draw on to cope (Hobfoll et al., 2018). Ghafoor and Haar (2021) argue that employees with greater individual resources can draw on their resource reservoir and, therefore, manage experiences more advantageously. High burnt-out risk represents a state where resources are critically low-the reservoir of resources is "empty"-and workers with high burnt-out risk have a critical shortage of resources. Hence, they become fragile and seek ways to minimize the drain on resources. Specifically, removing themselves from their job to escape the resource loss condition. Indeed, the COR theory has become a central theoretical approach to studying burnout (Moin et al., 2020), including using the BAT (see Otto et al., 2021; Urbanaviciute et al., 2021).

## 3 | HYPOTHESES

Haar (2021) states that high burnt-out risk represents situations/instances where "burnout has become so intense that it severely affects workers" (p. 5). Initial evidence for burnt-out risk has been modest, with Schaufeli et al. (2020b) reporting a 5% rate in a large sample from the Netherlands, and 8% among Belgium employees. Haar (2021) reported a much higher rate at 11.3%, although he argued the focus on managers might explain that. The earlier studies are all pre-Covid-19 times, and Haar's (2021) data collection was before New Zealand's first lockdown. The psychological trauma associated with national lockdowns (Constantin et al., 2021) would represent a resource drain under the COR theory and, thus, it is expected that burnt-out risk levels will be higher. Further, managers are likely to have different levels compared to employees, and hence two samples are tested here: (1) employees and (2) managers. This is because Haar et al. (2018) argue that managers have jobs with greater complexities than employees with additional challenges. Furthermore, Roche et al. (2014) note that managers face greater workplace challenges and complexities, presenting them with

stronger tests on their well-being. Under the COR theory, we expect managers to report higher rates of burnt-out risk than employees.

*Hypothesis 1: Managers will report higher burnt-out risk rates than employees.*

### 3.1 | Burnt-out and turnover intent

The BAT has been positively linked to turnover intentions, with Sakakibara et al. (2020) finding the four BAT dimensions were all positively related to turnover intentions among a large sample of Japanese workers ($0.53 > r > .36$, all $p < .001$). Their resulting structural equation model showed that BAT was a strong predictor of turnover intentions. Similarly, Schaufeli et al. (2020b) reported that BAT burnout had a strong direct effect on turnover intentions ($\beta = .44$, $p < .001$) using a sample of 1500 employees from the Netherlands. Apart from these two studies, the links between BAT and turnover intentions are limited. Under the COR theory, burnt-out risk reflects a critically low level of resources. Principle 4 of the COR theory (the desperation principle) is defined as, "when people's resources are outstretched or exhausted, they enter a defensive mode to preserve the self which is often defensive, aggressive, and may become irrational" (Hobfoll et al., 2018; p. 106). Here, it is suggested that high burnt-out risk reflects the lowest levels of resources, and this should trigger COR Principle 4 and see employees flee their jobs. Both employees and managers are expected to react similarly to being burnt-out.

*Hypothesis 2: (a) Employees and (b) managers who self-report burnt-out risk will report greater turnover intentions.*

### 3.2 | Leadership

Next the role of leadership is explored, specifically supervisor organizational embodiment (SOE). Eisenberger et al. (2010) argue SOE reflects employee perceptions "concerning the extent of their supervisor's shared identity with the organization" (p. 2). Thus, SOE reflects how associates view their supervisors' values and motives, and how they align with the organization (Eisenberger et al., 2014). Eisenberger et al. (2014) argue that it is important to consider SOE because it embodies the leader's power and influence. If an employee feels that praise from their leader reflects praise from their organization, the effects will likely be more beneficial (see Eisenberger et al., 2014). Shoss et al. (2013) found SOE significantly moderated the effect of abusive supervision, leading to intensified detrimental effects. Here, it is expected that employees and managers with high SOE will be more likely to leave their job when burnt-out. This reflects they will see their leader (and organization) as having allowed their worker to achieve such a burnt-out state. In this regard, the SOE will reinforce COR Principle 4 because the worker will see their organization as having facilitated this in some manner (e.g., a heavy workload), thus, encouraging the burnt-out worker to escape their job.

*Hypothesis 3: SOE will moderate burnt-out effects for (a) employees and (b) managers with higher turnover intentions when SOE is high.*

## 4 | METHODS

### 4.1 | Participants and sample

Data were collected in May 2020 using a Cint New Zealand employee survey panel (see Haar, 2021 for more details). Cint is a platform that provides businesses and researchers access to a wide and representative sample of individuals. This panel study had three qualifiers: (1) being in paid work; (2) working 20 h/week minimum; and (3) being either an employee or manager. Overall, $N = 709$ employee respondents and $N = 313$ manager respondents were achieved. Panels are becoming more common (see Haar, 2021) and nondifferent from conventional mail-out survey data (see Walter et al., 2019). Overall, respondents were more likely to be female in the employee sample (59%) and male in the manager sample (57%). The employee sample had an average age of 39.8 years ($SD = 14.3$), like the manager sample of 38.2 years ($SD = 12.8$). By sector, employee/manager respondents came from mainly the private sector (60.4%/73.2%), followed by the public sector (34.6%/21.7%), and not-for-profit sector (5.1%/5.1%). Both samples had wide and varied occupations, with employees including barista, meat inspector, teachers, farmers, office workers, and nurses, with managers including business owners, directors, country manager, and director legal services.

### 4.2 | Measures

This study focuses on dichotomous variables to enable us to calculate odds ratios with respect to burnt-out risk-turnover. All reliabilities are reported employee/manager data.

*Job Burnout* was measured using the 23-items of the BAT scale (Schaufeli et al., 2020a), coded 1 = never to 5 = always. The four core symptoms of burnout are exhaustion (8-items, e.g. "I want to be active at work, but somehow I am unable to manage", $\alpha = .91/.92$), mental distance (5-items, sample "I struggle to find any enthusiasm for my work," $\alpha = .85/.87$), emotional impairment (5-items, sample "I get upset or sad at work without knowing why," $\alpha = .90/.93$), and cognitive impairment (5-items, sample "At work I struggle to think clearly," $\alpha = .92/.94$). Schaufeli et al., (2020a, 2020b) argued that the BAT dimensions can be combined if they are highly correlated. The present study showed within the employee sample these four dimensions correlated highly (lowest $r = .58$ and highest $r = .69$). This was similar for the manager sample (lowest $r = .69$ and highest $r = .81$). This was confirmed through conducting confirmatory factor analysis (CFA) in AMOS (version 26), which aligned with the BAT factor structure. Guidelines for goodness-of-fit indices were followed (e.g., Hu & Bentler, 1998; Williams et al., 2009): (1) the comparative fit index (CFI ≥ 0.90); (2) the Tucker-Lewis index (TLI ≥ 0.90); (3) the

root-mean-square error of approximation (RMSEA ≤ 0.08); and (4) the standardized root mean residual (SRMR ≤ 0.10). This resulted in a good fit for the data (four BAT dimensions, correlated with each other) for the employee sample: $\chi^2(df) = 923.4(224)$, TLI/CFI = 0.94, RMSEA = 0.07, and SRMR = 0.05 and the manager sample: $\chi^2(df) = 615.4(224)$, TLI/CFI = 0.94, RMSEA = 0.08, and SRMR = 0.06. Similarly, the higher-order model (four BAT dimensions loading onto a single job burnout factor) was also an excellent fit for the employee sample: $\chi^2(df) = 966.1(229)$, TLI/CFI = 0.93, RMSEA = 0.07, and SRMR = 0.06 and the manager sample: $\chi^2(df) = 629.5(224)$, TLI/CFI= 0.93, RMSEA = 0.08, and SRMR = 0.06. The overall combined construct (see Hadzibajramović et al., 2020) produced a very robust job burnout scale ($\alpha$ = .95/.97).

*Burnt-Out Risk* was calculated from the above burnout scale. Schaufeli et al., (2020a, 2020b) provide a burnt-out score of ≥ 3.30, which was calculated using Rasch analysis (see Hadzibajramović et al., 2020). 1 = burnt-out if job burnout mean ≥ 3.30, otherwise a score of 0 = not burnt-out.

Turnover Intentions were measured using the four-item scale by Kelloway et al. (1999), coded 1 = strongly disagree, 5 = strongly agree. A sample item is "I don't plan to be at my organization much longer" ($\alpha$ = .93/.91). This construct is then used to create a dummy variable focusing on high turnover intentions only (like Virtanen et al., 2002) where they focused on the top 25% of an outcome. *High Turnover Intentions* was calculated via a cutoff ratio of mean+1*SD* (here 1 = mean > 3.75 for employees and mean> 3.87 for managers, and 0 = all other values). Overall, this represents the top 15.8%/18.8% of respondents (employees/managers). This value reflects those scoring the highest levels of turnover intentions and enables calculating odds ratios of high turnover intent when respondents have high burnt-out risk.

SOE was measured using the 5-item scale by Eisenberger et al. (2014), coded 1 = strongly disagree, 7 = strongly agree. A sample item is "When my supervisor compliments me, it is the same as my organization complimenting me" ($\alpha$ = .89/.87). *High SOE* was calculated via a cutoff ratio of mean+1*SD* (1 = mean > 4.40 for employees and mean > 4.62 for managers, and 0 = all other values). Overall, this represents the top 18.3%/15.3% of respondents (employees/managers).

### 4.3 | Controls variables

Given the literature has acknowledged that job satisfaction plays a critical role in turnover intentions (see Li et al., 2016), including meta-analysis support (see Griffeth et al., 2000), this was controlled for. *High Job Satisfaction* was measured using three items from Judge et al. (2005), coded 1 = strongly disagree, 5 = strongly agree. This measure has been well-validated (Haar et al., 2014) and has good reliability ($\alpha$ = .89/.88). The high value was calculated as above, with mean+1 *SD* (here 1 = mean > 4.52 for employees and mean > 4.67 for managers, and 0 = all other values). Overall, this represents the top 14.7%/18.5% of respondents (employees/manager). Demographics were also controlled for: *Age* (in years) and *Job Tenure* (in years) due to meta-analytic links (Griffeth et al., 2000; Ng & Feldman, 2010). Finally, perceived job mobility is controlled for because empirical evidence shows it is positively linked to turnover intent (e.g., Haar et al., 2021; Tepper, 2000). *High Job Mobility* was measured using the 2-item scale by Tepper (2000), 1 = strongly disagree, 5 = strongly agree. Following Haar et al. (2021) another item was added, "I know there are similar jobs available to me outside my organization," to address labor market contextual factors (Forrier et al., 2009). Exploratory factor analysis (principal axis factoring, direct oblimin) was conducted, and all items loaded onto a single factor (eigenvalues of 1.42/1.38, employee/manager), accounting for sizeable amounts of variance (71.0%/68.8%, employee/manager) and achieving good reliability ($\alpha$ = .79/.80 employee/manager). Again, calculated at mean +1 *SD* (here 1 = mean > 4.04 for employees and mean > 4.23 for managers, and 0 = all other values). This represents the top 9.4%/15.7% of employee/manager respondents.

### 4.4 | Measurement models

Study constructs were confirmed using CFA in AMOS (version 26) using above thresholds. The CFA included all the full measures noted above. Overall, the hypothesized measurement model was the best fit for the employee sample: $\chi^2(df)$ =2 248.2(654), TLI/CFI = 0.92, RMSEA = 0.06, and SRMR = 0.05 for the, and manager sample: $\chi^2(df) = 1403.3(654)$, TLI/CFI = 0.92, RMSEA = 0.06, and SRMR = 0.06. Alternative measurement models, where various alternative CFA combinations were explored (e.g., turnover intentions and job mobility) all resulted in a poorer fit (all $p < .001$).

### 4.5 | Analysis

Hypothesis 1 was tested with a *t* test in SPSS (version 26). Hypotheses 2 and 3 were tested in SPSS using binary regression, using bootstrapping (5000 times), providing confidence intervals. The logic of Carsten and Spector (1987) is drawn on, whereby control variables that are individual factors (e.g., demographics) are separated from work factors (attitudes) respectively. Thus, control variables were entered in Blocks 1 (age, tenure) and 2 (job mobility and job satisfaction), burnt-out risk in Block 3, SOE in Block 4, and the interaction (burnt-out risk x SOE) in Block 5. For breakdowns of group compositions, *t* tests were conducted.

## 5 | RESULTS

Descriptive statistics for the study variables are shown in Table 1.

Table 1 shows that the overall job burnout construct, and burnt-out risk, are all significantly correlated to turnover intentions and high turnover intentions (all $p < .01$). The analysis showed 8% of employee respondents reported high burnt-out risk while in the managers

**TABLE 1** Correlations and descriptive statistics of study variables

| Variables | Employee sample Mean | Employee sample *SD* | Manager sample Mean | Manager sample *SD* | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Age | 39.8 | 14.3 | 38.2 | 12.8 | -- | .51‡ | −.15‡ | −.08 | .13* | .02 | .06 | −.02 | −.31‡ | −.21‡ | −.28‡ | −.11 |
| 2. Tenure | 5.70 | 5.80 | 7.13 | 5.73 | .54‡ | -- | −.10 | −.02 | .05 | −.01 | −.08 | −.07 | −.11 | −.02 | −.15‡ | −.02 |
| 3. JM | 3.10 | .94 | 3.25 | .98 | −.21‡ | −.10* | -- | .61‡ | .01 | −.05 | .12* | .13* | .12* | .11* | .34‡ | .20‡ |
| 4. High JM | .09 | .29 | .16 | .36 | −.07 | −.00 | .55‡ | -- | .13* | .16‡ | .13* | .21‡ | −.01 | .04 | .20‡ | .24‡ |
| 5. JS | 3.56 | .96 | 3.70 | .97 | .20‡ | .11‡ | .01 | .02 | -- | .59‡ | .47‡ | .29‡ | −.33‡ | −.23‡ | −.40‡ | −.29‡ |
| 6. High JS | .15 | .35 | .19 | .39 | .22‡ | .14‡ | −.05 | .07 | .58‡ | -- | .29‡ | .35‡ | −.27‡ | −.13* | −.33‡ | −.13* |
| 7. SOE | 3.62 | .79 | 3.87 | .75 | .05 | −.01 | −.02 | −.03 | .38‡ | .24‡ | -- | .59‡ | −.03 | .02 | −.23‡ | −.20‡ |
| 8. High SOE | .18 | .39 | .15 | .36 | −.04 | −.02 | −.02 | .05 | .26‡ | .27‡ | .67‡ | -- | −.07 | −.00 | −.18‡ | −.09 |
| 9. Job Burnout | 2.34 | .68 | 2.43 | .83 | −.35‡ | −.14‡ | .10‡ | .07 | −.46‡ | -.33‡ | −.24‡ | −.15‡ | -- | .76‡ | .46‡ | .37‡ |
| 10. B-OR | .08 | .28 | .17 | .38 | −.18‡ | −.09* | .05 | .11‡ | −.25‡ | −.10‡ | −.10‡ | −.05 | .61‡ | -- | .38‡ | .37‡ |
| 11. TI | 2.59 | 1.16 | 2.70 | 1.17 | −.25‡ | −.19‡ | .22‡ | .17‡ | −.53‡ | −.38‡ | −.26‡ | −.17‡ | .45‡ | .27‡ | -- | .68‡ |
| 12. High TI | .16 | .37 | .19 | .39 | −.14‡ | −.08* | −.19‡ | .26‡ | −.39‡ | −.14‡ | −.16‡ | −.08* | .24‡ | .26‡ | .66‡ | -- |

*Note*: $N = 709$ employees (below diagonal), and $N = 313$ managers (above diagonal).

Abbreviations: B-OR, burnt-out risk; JB, job mobility; JS, job satisfaction; TI, turnover intentions.

*$p < .05$.

‡$p < .01$.

sample, this was 17%, supporting Hypothesis 1. Results of the odds ratio (from the binary regression) are shown in Table 2 (both employee/manager samples).

Table 2 shows that significant odds ratios are found for employees with high job mobility (631.4%, $p < .001$), with 45% of those in the high turnover intentions group, compared to only 13% of employees outside of this category. The second control variable of high job satisfaction also had a significant odds ratio (76.2%, $p = .010$) representing lower turnover intent. Hypothesis 2 explored burnt-out risk toward high turnover intentions, this was supported. A significant odds ratio was found (327.8%, $p < .001$), showing those employees with high burnt-out risk are 47% likely to occupy the high turnover intent group, compared with 13% of employees not in the burnt-out risk group. High SOE also had a significant odds ratio to high turnover intentions (55.9%, $p = .047$) or *less* likely to be in the high turnover intent group. Importantly, and in support of Hypothesis 3, high SOE interacted with burnt-out risk (862.0%, $p = .031$), and the interaction is shown in Figure 1.

The interaction shows that employees who are not at burnt-out risk have low levels of turnover intent probability, which is significantly lower for respondents with high SOE (5.9% turnover intent probability) than those with low SOE (12.4% turnover intent probability). However, when compared with respondents who are in the high burnt-out risk group, the differences are extremely different. Those with low SOE have a much lower probability of turnover intent (31.8%), while those with high SOE are much higher, with a turnover intent probability of 63.9%. This supports the argument around high SOE being detrimental among burnt-out risk employees.

Table 2 shows that for the manager sample, significant odds ratios are found for those with high job mobility (670.7%, $p < .001$), showing that 41% of managers with high mobility are in the high turnover intentions group, compared with only 15% of managers outside of this category. Interestingly, the second control variable of high job satisfaction is not significant ($p = .133$). Hypothesis 2 explored burnt-out risk toward high turnover intentions, and this was significant (760.3%, $p < .001$), showing those managers with high burnt-out risk occupy the high turnover intent group at 52%, compared to only 12% of managers in the non-burnt-out risk group. High SOE was not significant ($p = .107$) and did not have a significant interaction effect ($p = .882$). Both models were significant, accounting for 21%/29% of the variance toward high turnover intent in the employee/manager samples.

## 6 | DISCUSSION

The present study used the BAT and the assessment of burnt-out risk to calculate odds ratios around high turnover intentions. Two New Zealand samples were used, reflecting representative samples across sectors, industries, and professions. The focus on employees and managers reflects strong attention in the literature around managers facing different challenges than employees (e.g., Haar et al., 2018; Haar, 2021). Indeed, managers reported a 17% burnt-out risk rate compared to 8% for employees. Thus, managers are twice as likely to be in the high burnt-out risk group as employees. This possibly reflects the pressures faced by organizational leaders in today's challenging times. The present study included strong control variables based on meta-analyses around demographics (Griffeth et al., 2000; Ng & Feldman, 2010) and job satisfaction (Griffeth et al., 2000; Li et al., 2016), and included job mobility (e.g., Haar

**TABLE 2** Odds ratios towards high turnover intentions (both samples)

| Variable relationships | Employee sample<br>Odds ratio | High turnover intentions percentages (by groups) | Confidence intervals | *p* value |
|---|---|---|---|---|
| Control variables | | | | |
| Age | .988 | n/a | LL = 0.97, UL = 1.01 | *p* = .247 |
| Tenure | .981 | n/a | LL = 0.93, UL = 1.04 | *p* = .482 |
| High job mobility | 6.314 | High mobility = 45%, Rest = 13% | LL = 3.46, UL = 11.53 | *p* < .001 |
| High job satisfaction | .238 | High satisfaction = 4%, Rest = 18% | LL = 0.08, UL = 0.71 | *p* = .010 |
| Predictor | | | | |
| Burnt-out | 3.278 | Burnt-out = 47%, Rest = 13% | LL = 1.71, UL = 6.27 | *p* < .001 |
| Moderator | | | | |
| High SOE | .441 | High SOE = 10%, Rest = 17% | LL = 0.20, UL = 0.99 | *p* = .047 |
| Interaction | | | | |
| Burnt-out × High SOE | 8.620 | See Figure 1. | LL = 1.22, UL = 60.82 | *p* = .031 |
| Nagelkerke R square | .21 | −2 Log Likelihood = 525.3(*p* < .001) | | |
| **Variable relationships** | **Manager Sample<br>Odds ratio** | **High turnover intentions percentages (by groups)** | **Confidence intervals** | ***p* value** |
| Control variables | | | | |
| Age | .996 | n/a | LL = 0.97, UL = 1.03 | *p* = .792 |
| Tenure | .990 | n/a | LL = 0.92, UL = 1.06 | *p* = .766 |
| High job mobility | 6.707 | High mobility = 41%, Rest = 15% | LL = 3.01, UL = 14.97 | *p* < .001 |
| High job satisfaction | .419 | n/a | LL = 0.13, UL = 1.30 | *p* = .133 |
| Predictor | | | | |
| Burnt-out | 7.603 | Burnt-out = 52%, Rest = 12% | LL = 3.53, UL = 16.39 | *p* < .001 |
| Moderator | | | | |
| High SOE | .107 | n/a | LL = 0.05, UL = 1.33 | *p* = .107 |
| Interaction | | | | |
| Burnt-out × High SOE | 1.194 | n/a | LL = 0.11, UL = 12.49 | *p* = .882 |
| Nagelkerke R square | .29 | −2 Log Likelihood = 240.3(*p* < .001) | | |

*Note*: n/a = indicates no calculations required because no significant differences exist.

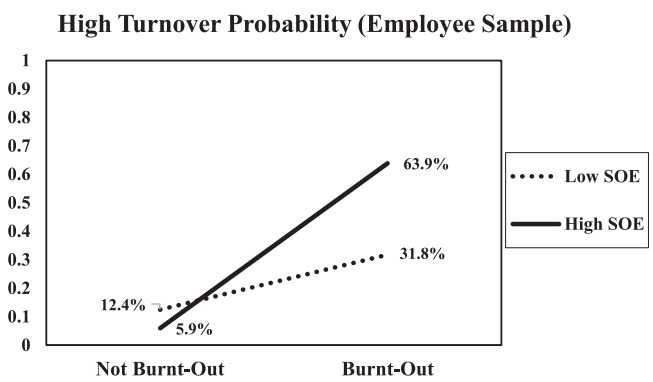


**FIGURE 1** Probability of high turnover from being burnt-out moderated by high supervisor organizational embodiment (SOE).

et al., 2021; Tepper, 2000). From the control variables, the effects of job satisfaction and job mobility are significant predictors in the models. Importantly, even though the odds of high mobility and high job satisfaction were important determinants of high turnover intentions, high burnt-out risk still had over a three times probability of driving employees to leave their job.

Interestingly, in the manager sample toward high turnover intentions, high job mobility had a high odds ratio while job satisfaction was nonsignificant. This suggests that for managers, having better opportunities and being desirable in the job marketplace outweighs the influence of liking the job. Nevertheless, the odds of managers leaving are heavily impacted by burnt-out risk, with odds of 760%-over double that of employees. However, high burnt-out risk *and* being in the high turnover intent category was high among both employees (47%) and managers

(52%). This supports the COR theory that burnt-out risk represents the highest form of resource losses triggering Principle 4, thus, encouraging employees and managers to flee their jobs. It also aligns theoretically with the BAT being a diagnostic tool for examining important workplace outcomes (Schaufeli et al., 2020a, 2020b). Further, by calculating high turnover intent via a cutoff score (mean+ 1 *SD*), the present study can show the immense influence of burnt-out risk on high turnover intentions.

Further, how an employee perceives their treatment from their supervisor as coming from the organization (Eisenberger et al., 2010) is important. Under the COR theory, this represents another resource lost-a lack of positive support from the supervisor (Hobfoll et al., 2018). Indeed, the interaction effects show the probability of turning over at the lowest levels (5.9%) when employees have high SOE but are not burnt-out but increasing to 63.9% among burnt-out respondents (over 10 times higher). A similar effect was not found with managers. This could indicate that managers see their bosses and SOE slightly differently, perhaps because managers themselves play a role in shaping SOE, whereas employees do not. Overall, the addition of SOE extends both the BAT and turnover literature, especially among employees, where SOE had a significant direct effect on high turnover intentions.

## 6.1 | Implications

Important HR implications include addressing burnout causes as an important step, such as job insecurity and workload, which are strong antecedents (Aronsson et al., 2017; Sakakibara et al., 2020). Job complexity (Walmsley et al., 2018) can also be a burden on employees and managers, and warrants attention. Regarding the cost of turnover, even controlling for mobility and satisfaction, managers were 7.6 times more likely to leave with a high burnt-out risk. Hence, training and development around workload sizing is vital for managers. Further, recognizing the additional complexities and challenges they face (Haar et al., 2018; Roche et al., 2014) is key. Ensuring managers get sufficient time off to switch off and recuperate is important, as is addressing technological issues (24/7 access to work). Finally, HR Managers might find the BAT a useful tool within current climate surveys to understand the burnout risk of their workforce and highlighting important drivers. Identifying staff with high burnt-out risk might provide HR with the opportunity to intervene and remedy the employee's well-being before they leave.

Researchers are encouraged to further compare burnt-out rate between employers and managers, explore SOE, and other forms of support and leadership. Understanding the differences between managers and employees regarding resource losses (e.g., job complexity) but also resource gains (e.g., job control) might be especially worthwhile. Studies exploring not only workload, and particular factors like technology and being tethered to the office (see Traylor et al., 2021) would be useful. Longitudinal studies to establish causality of these relationships are encouraged. Exploring other outcomes (e.g., OCBs, engagement) using odds ratios could provide useful insights. Furthermore, exploring other moderators is encouraged given their support in the literature (see Alarcon, 2011).

**TABLE 3** Regression analysis towards turnover intentions (both samples)

| Variable relationships | Employee sample $\beta$ (*SE*) | Confidence intervals | *p* value |
|---|---|---|---|
| Control variables *I* ($r^2\Delta$): | .07 | | $p < .001$ |
| Age | -.02(0.00) | LL = -.02, UL = -.01 | $p < .001$ |
| Tenure | -.02(0.01) | LL = -.03, UL = 0.00 | $p = .059$ |
| Control variables II ($r^2\Delta$): | .28 | | $p < .001$ |
| Job mobility | .24(0.04) | LL = 0.17, UL = 0.32 | $p < .001$ |
| Job satisfaction | -.62(0.04) | LL = -.69, UL = -.54 | $p < .001$ |
| Predictor ($r^2\Delta$): | .04 | | $p < .001$ |
| BAT Burnout | .38(0.04) | LL = 0.26, UL = 0.49 | $p < .001$ |
| Moderator ($r^2\Delta$): | .00 | | $p = .064$ |
| SOE | -.09(0.05) | LL = -.18, UL = 0.01 | $p = .064$ |
| Interaction ($r^2\Delta$): | .00 | | $p = .429$ |
| BAT burnout × SOE | -.03(0.04) | LL = -.10, UL = 0.04 | $p = .429$ |
| R square | .38 | $F = 61.949$ ($p < .001$) | |
| **Variable relationships** | **Manager Sample $\beta$ (*SE*)** | **Confidence intervals** | ***p* value** |
| Control variables I ($r^2\Delta$): | .08 | | $p < .001$ |
| Age | −.02 (0.01) | LL = −.04, UL = −.01 | $p < .001$ |
| Tenure | −.00 (0.01) | LL = −.03, UL = 0.02 | $p = .794$ |
| Control variables II ($r^2\Delta$): | .23 | | $p < .001$ |
| Job mobility | .37 (0.06) | LL = 0.26, UL = 0.49 | $p < .001$ |
| Job satisfaction | −.46 (0.06) | LL = −.58, UL = −.35 | $p < .001$ |
| Predictor ($r^2\Delta$): | .07 | | $p < .001$ |
| BAT burnout | .41 (0.07) | LL = 0.27, UL = 0.55 | $p < .001$ |
| Moderator ($r^2\Delta$): | .02 | | $p = .002$ |
| SOE | −.25 (0.08) | LL = −.41, UL = −.09 | $p = .002$ |
| Interaction ($r^2\Delta$): | .00 | | $p = .931$ |
| BAT burnout ×SOE | −.01 (0.05) | LL = -.11, UL = 0.10 | $p = .931$ |
| R square | .40 | $F = 28.776$ ($p < .001$) | |

*Note*: All significance tests were two-tailed. Confidence intervals are 95%. Abbreviations: $\beta$, unstandardized regression coefficients; BAT, Burnout Assessment Tool; LL, lower limit; SOE, supervisor organizational embodiment; UL, upper limit; SE , standard error.

## 7 | LIMITATIONS

Issues around common method variance (CMV) exist although by using two distinct samples this is somewhat alleviated. It is also acknowledged that while burnout influences turnover theoretically, this study does not provide causality. Further, using CFA and testing

alternative CFAs adds assurance (see Haar et al., 2014). The CFA analysis shows the measures are robust across both samples including the new BAT measure. Overall, almost all central variables correlate significantly in the expected direction with turnover intentions in both samples, enhancing confidence in the findings (Nuzzo, 2014). That said, beyond the direct effects of burnt-out risk on turnover, there were differences in the manager sample including a lack of significant effects from job satisfaction, SOE, and the interaction. This suggests likely differences in the manager sample and should encourage further focus on this group. Further,

Evans (1985) found CMV issues were rare in the presence of significant moderation effects, which was found here (employee sample). While differences between managers and employees were found, the nature of these differences (e.g., job complexity) was not captured, and would have provided useful insights into why managers' burnt-out risk was much higher. Further, given the analysis here focuses on dichotomous variables for all key measures, Table 3 provides the regression analysis using all continuous variables. Another potential issue is that while Rasch analysis (see Hadzibajramović et al., 2020) was used to establish the cut-off for high burnt-out risk, the high turnover intentions threshold is set within each sample here (employee vs. manager). Hence, these cut-off values are sample specific and should not be considered as a set guideline. Overall, two distinct samples with large and representative samples of New Zealand employees/managers were used, providing confidence in the generalizability of the findings.

## 8 | CONCLUSION

Burnt-out risk impacts high turnover intentions, and especially so for managers. Importantly, this was after controlling for strong correlates of turnover intentions. Not only do managers' report high levels of burnt-out risk, but they are also more likely to be driven to leave. Given the high cost of turnover for organizations, and the links to poor firm performance (Park & Shaw, 2013), addressing job burnout in general-and especially for managers-is clearly warranted. Given current Covid-19 challenges, firms must be proactive toward workforce well-being.

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### CONFLICT OF INTEREST

The author declares no conflict of interest.

### DATA AVAILABILITY STATEMENT

Data is available from the author.

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