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The Short Burnout Measure (SBM): Development and Validation

Escala Breve de Burnout (SBM): desarrollo y validación

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Abstract

Background: Burnout is a widespread issue in organizational settings, negatively affecting both employees and organizations. While numerous scales have been developed, many have limitations, such as failing to differentiate between depersonalization and cynicism, or using reverse items to assess inefficacy, that compromise their validity and utility. **Objective**: to develop and validate a short burnout measure (SBM). **Method**: An instrumental study was conducted using a sample of 1256 information technology (IT) workers from Argentina (56.1% males; age range: 18-59, M = 25.16). Participants completed an online survey including the SBM, along with measures of turnover intention and employee Net Promoter Score. **Results**: Confirmatory factor analysis comparing one-factor, three-factor, four-factor, higher-order, and bifactor models revealed that the four-factor model –comprising exhaustion, cynicism, depersonalization, and inefficacy– provided the best fit to the data [$\chi^2(14) = 26.60$, $p < .05$, CFI = .998, TLI = .996, RMSEA = .038 (90% CI [.014, .06]), WRMR = 0.33]. All SBM factors demonstrated satisfactory construct reliability (H coefficients ranging from .77 to .88). Criterion validity was supported by theoretically consistent associations found between SBM dimensions, turnover intention, and employee Net Promoter Score. **Conclusion**: This study presents a new scale that overcomes key limitations of existing self-report measures by using separate subscales for assessing cynicism and depersonalization and using direct items to assess inefficacy. These features, together with its brevity, make the SBM a practical and psychometrically sound tool for rapidly assessing burnout in IT workers. Study limitations and the need to replicate these findings in different occupational sectors are discussed.

Keywords: burnout, organization, scale construction, factorial validity, short measure.

Resumen

Antecedentes: actualmente existen diferentes instrumentos para medir el burnout. Sin embargo, ciertas limitaciones como la falta de diferenciación entre cinismo y despersonalización, o el uso de ítems invertidos para evaluar la ineficacia profesional, afectan la validez y la utilidad de estas medidas. **Objetivo**: desarrollar y evaluar las propiedades psicométricas de una escala breve de burnout (*Short Burnout Measure*; SBM). **Método**: se realizó un estudio empírico de tipo instrumental con 1256 trabajadores argentinos del sector de tecnologías de la información (IT) (56.1% hombres, rango de edad 18-59, M = 25.16). Los participantes completaron una encuesta online que incluía la SBM, junto con medidas de intención de abandonar la organización y de recomendación de trabajar en la empresa. **Resultados**: el análisis factorial confirmatorio mostró que un modelo de cuatro factores, representado por agotamiento, cinismo, despersonalización e ineficacia profesional, presentó un ajuste excelente a los datos [$\chi^2(14) = 26.60$, $p < .05$, CFI = .998, TLI = .996, RMSEA = .038 (IC 90% [.014, .06]), WRMR = .33], y fue superior a los modelos de uno y tres factores, así como a los modelos jerárquicos y bifactor. La fiabilidad de constructo fue adecuada (coeficientes H entre .77 y .88) y se observaron las relaciones teóricas esperadas entre los factores de la SBM, la intención de abandonar la organización y la recomendación de trabajar en la empresa. **Conclusión**: este estudio ofrece un nuevo instrumento que supera algunas limitaciones presentes en otras escalas, al evaluar separadamente los componentes de cinismo y despersonalización, y al utilizar ítems directos para medir la ineficacia profesional, evitando los problemas psicométricos asociados al uso de ítems directos e invertidos. Estas características, junto con su brevedad, convierten al SBM en una medida alternativa útil para evaluar de forma rápida y eficiente el burnout en trabajadores del sector IT. Se discuten las limitaciones del estudio y la necesidad de replicar los resultados en trabajadores de diferentes sectores ocupacionales.

Palabras clave: burnout, organización, validez factorial, escala, análisis factorial confirmatorio.

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Introduction

Burnout is a pervasive issue in organizations and has become more prevalent in recent years (Maslach & Leiter, 2017). The COVID-19 pandemic has steadily increased the incidence of burnout across many industries, due to its impact on working conditions (Gabriel & Aguinis, 2022). In particular, the widespread adoption of teleworking has blurred the boundaries between work and home life, increasing work hours and work-family conflict (Trógolo et al., 2022). Additionally, the continuous connection to work through smartphones and other work-related technological devices has heightened perceived workplace telepressure, reducing the opportunity for psychological detachment from work and recovery (Franzen, 2020). The insufficient technology-related skills and training for remote work has also placed additional stress on workers, especially older employees who may struggle to adapt to new communication technologies (Loreg, 2020). Importantly, teleworking and increased use of work-related technologies have become the «new normal» in many organizations in the post-COVID era (Raghavan et al., 2021). Therefore, in order to protect health and well-being it is essential to have brief and psychometrically sound measurement tools that allow employers to frequently evaluate and monitor workers' health and identify those who are at greater risk of developing burnout.

Despite the development of various burnout measures over the years –such as the Maslach Burnout Inventory (MBI; Maslach & Jackson, 1981), the Maslach Burnout Inventory-General Survey (MBI-GS; Schaufeli et al., 1996), the Oldenburg Burnout Inventory (OLBI; Demerouti et al., 2003), the Copenhagen Burnout Inventory (CBI; Kristensen et al., 2005), the Shirom-Melamed Burnout Measure (SMBM; Shirom & Melamed, 2006), and the Burnout Assessment Tool (BAT; Schaufeli et al., 2020)– these measures have conceptual, technical, and psychometric limitations that potentially hinder further progress in burnout theory and research. The present study addresses the need for alternative, well-validated measures. We begin by outlining the conceptual and psychometric shortcomings of the most widely used burnout measures and demonstrate the need for new scales. We then present the development of a new scale, along with evidence supporting its validity and reliability.

The concept and measurement of burnout

Burnout is most commonly defined as a three-dimensional, work-related syndrome characterized by exhaustion, cynicism and reduced self-efficacy (Maslach & Leiter, 2021). Exhaustion refers to feelings of being emotionally and physically drained. Cynicism represents an indifferent, distant attitude towards work. Finally, reduced self-efficacy, also referred to as a low sense of personal accomplishment, is characterized by a negative self-evaluation of one's capability to perform work well. The most widely used instrument for assessing burnout is the Maslach Burnout Inventory (MBI; Maslach & Jackson, 1981), originally developed to human services professionals. As the understanding of burnout expanded to include workers in all professions, the concept of burnout was broadened. In response, the Maslach Burnout Inventory–General Survey (MBI-GS; Schaufeli et al., 1996) was created to assess the same three burnout dimensions, using more general worded items that apply to a broader range of workers. Because of its generic nature and greater applicability, the MBI-GS has become the gold standard for burnout research (De Beer et al., 2024).

The MBI-GS: Review of empirical evidence

Extensive research on the factorial validity of the MBI-GS has confirmed its three-factor structure, as well as its invariance across diverse occupational groups and countries (Bravo et al., 2021; Bria et al., 2014; Juárez et al., 2020; Merino-Soto et al., 2023; Wang et al., 2024). However, some studies found support for the three-dimensional model only after incorporating modifications, such as eliminating items (Bria et al., 2014), allowing error correlation between items or allowing items to load on different factors (for a review, see De Beer et al., 2024). Additionally, alternative two –and four– factor models have also shown empirical support (Pando et al., 2015; Worley et al., 2008; Spontón et al., 2019). Thus, the factorial validity of the MBI-GS is not fully established. Another concern involves the internal consistency reliability of the MBI-GS factors, which tends to be modest across studies (De Beer et al., 2024). Further, some notable psychometric issues may limit the utility of the MBI-GS for research purposes, particularly its operationalization of the self-efficacy dimension and the inclusion of only cynicism, excluding depersonalization. These issues are further discussed below.

Efficacy versus inefficacy

A key controversial issue in burnout theory and research is the role of professional inefficacy. As noted by Edú-Valsania et al. (2022), while exhaustion and cynicism are strongly correlated, inefficacy shows weak correlations with these dimensions. Additionally, confirmatory factor analyses found that a model in which inefficacy loads onto a general burnout factor did not fit the data well. Instead, a two-factor model consisting of exhaustion and cynicism provided the best fit (Schaufeli et al., 2002, 2006; citation omitted, 2019). As a result, some scholars have argued that exhaustion and cynicism represent the «core» dimensions of burnout and have excluded inefficacy (Spontón et al., 2019; Fernández et al., 2020).

However, recent research has provided an alternative explanation for the role of inefficacy. Schaufeli and Salanova (2007) noted that exhaustion and cynicism, as operationalized by the MBI-GS, are measured using negatively-worded items, while inefficacy is measured with positively-worded self-efficacy items that are then reversed to indicate a lack of self-efficacy. This approach assumes that efficacy and inefficacy are perfectly negatively correlated (i.e., they are endpoints along a self-efficacy continuum), and consequently low scores on efficacy are deemed equivalent to inefficacy, and vice versa. However, these two dimensions are negatively but not perfectly correlated. As such, reversing efficacy items may lead to biased findings and an incorrect interpretation of inefficacy. Empirical tests have shown that a scale measuring inefficacy with negatively-worded items correlate more strongly with exhaustion and cynicism than the MBI-GS efficacy scale does. Moreover, a three-factor model, which includes exhaustion, cynicism, and inefficacy as distinct factors, fits the data better than the traditional three-factor model with the reversed self-efficacy scale (Bresó et al., 2007; Maroco et al., 2014; Morgan et al., 2014). These findings suggest that the divergent role of inefficacy reported in the literature may stem from item wording issues in the MBI-GS. Unfortunately, many applied researchers continue to use the original MBI-GS scale with the reversed self-efficacy subscale without addressing this issue.

Cynicism and depersonalization

The extension of the burnout concept to all occupations resulted in the replacement of the original MBI-depersonalization dimension by a cynicism scale to reflect a more general, detached attitude toward work rather than toward clients or coworkers. Depersonalization was thus eliminated from the further conceptualization and measurement of burnout, being considered a special case of «mental distancing» (Salanova et al., 2005). However, while cynicism and depersonalization can be both considered as expressions of mental distancing, they differ in their targets: depersonalization refers to distancing from service recipients, while cynicism refers to distancing from the job in general. Furthermore, the two dimensions are differently related to antecedents: depersonalization is related to high job demands whereas cynicism is related to poor job resources (Bakker et al., 2023). This evidence suggests that cynicism and depersonalization should be treated as distinct constructs. In support of this, Salanova et al. (2005) and Simbula and Guglielmi (2010) examined the empirical distinctiveness between these constructs and found that a four-factor model including depersonalization and cynicism as separate dimensions had a better fit than a three-factor model in which these dimensions are collapsed into a mental distancing factor. Thus, from both theoretical and empirical perspectives, exhaustion and cynicism appear to be distinct dimensions and should be assessed using separate scales.

Alternative measures of burnout

Several alternative burnout scales have been developed, such as the Oldenburg Burnout Inventory (OLBI; Demerouti et al., 2003), the Copenhagen Burnout Inventory (CBI; Kristensen et al., 2005), the Shirom–Melamed Burnout Measure (SMBM; Shirom & Melamed 2006) and the Burnout Assessment Tool (BAT; Schaufeli et al., 2020; for a review of other existing scales with limited application, see Edú-Valsania et al., 2022). While these instruments offer alternative ways of conceptualizing and measuring burnout, they also have important flaws. For example, the CBI assesses only exhaustion and includes non-work dimensions (e.g., personal burnout) that suggest burnout may be caused by factors outside the work domain, which conflicts with the prevailing view of burnout as a work-related syndrome. The SMBM only measures exhaustion, omitting cynicism, depersonalization, and inefficacy, thus neglecting the multifaceted nature of burnout. The SMBM consists of three scales assessing physical fatigue, emotional exhaustion, and cognitive weariness. Hence, it does not include cynicism, depersonalization and inefficacy, thus neglecting the multifaceted nature of burnout and can be considered as a measure of exhaustion. The OLBI includes exhaustion and disengagement from work –which is equivalent to cynicism– but fails to measure inefficacy, despite evidence supporting its inclusion as a burnout dimension (Bresó et al., 2007; Schaufeli & Salanova, 2007). Furthermore, the presence of both positively and negatively-worded items in the OLBI may result in psychometric problems, such as low reliability, underestimation of the association with other constructs, and spurious covariance among items that produce additional artificial factors (Gu et al., 2017). The BAT fails to include the inefficacy component and does not differentiate between depersonalization and cynicism. In addition, the underlying conceptualization of burnout includes secondary dimensions like depression and psychological distress, which overlap with symptoms of other mental disorders. This overlap complicates the interpretation of BAT scores and raises questions about its specificity for assessing burnout. Overall, the limitations of existing burnout measures highlight the need for continued improvement and development in this area.

Present study

To address the limitations of existing burnout measures, we developed the Short Burnout Measure (SBM). The SBM is based on a multidimensional conceptualization that includes exhaustion, cynicism and depersonalization as separate dimensions, along with a professional *in*efficacy scale (See Table 1). We also prioritized the development of a short scale, given the well-documented advantages of concise instruments, including increased participation, reduced respondent fatigue and cognitive overload, and improved data quality, which make assessments more efficient and precise (Dåderman et al., 2024). However, short scales can also present potential problems, such as lower internal consistency and reduced coverage of the breadth of the construct, which may subsequently reduce their content validity (Smith et al., 2000). Thus, the content validity, construct validity, and reliability of short scales must be rigorously tested, just as with longer scales.

Hence, this study has two objectives: (1) to develop a new, short 8-item burnout measure (SBM); and (2) to assess the psychometric properties of the new scale. Part 1 describes the scale development process, including the item selection strategy and expert ratings of the scale content. Part 2 presents evidence of the validity and reliability of the SBM.

Table 1
Description of the dimensions of the Short Burnout Measure

Exhaustion	Feeling of being overextended and drained of energy due to excessive job demands
Cynicism	Feeling detached and doubting the value or purpose of one's work
Depersonalization	Negative, callous, or excessive distancing attitudes toward people (co-workers and recipients of one's services)
Professional inefficacy	Feelings of incompetence and low sense of work achievement

Part 1. Scale development

Method

Procedure

Item selection strategy

To develop the SBM, we relied on the substantial body of literature supporting the internal validity of the Maslach Burnout Inventory (MBI) and the MBI-General Survey (MBI-GS). The following criteria were used to select the most appropriate items for retention:

(a) Factor loadings: Commonly used rules of thumbs suggest that standardized factor loadings ≥ .50 are acceptable (Goretzko et al., 2024). We adopted this criterion as the minimum threshold for item retention and prioritized those items with the highest loadings (λ) on their respective latent factors. Higher factor loadings indicate a stronger contribution of the item to the overall measurement of the construct. These items are considered to represent a more accurate measurement of the construct.

(b) Residual error variance: The residual error variance of the selected items should be independent of each other. Residual error variance refers to variance unexplained by the intended factor, which may be caused by random measurement error or issues with score reliability (Kline, 2023).

(c) Measurement invariance: The selected items should demonstrate invariance across different samples and occupational groups. Measurement invariance indicates the generalizability of the item's properties across populations and settings, allowing valid comparisons of the construct across groups (Meuleman et al., 2023).

Using these criteria, we aimed to select items that best captured each burnout dimension while demonstrating robust psychometric properties across diverse populations and contexts.

Literature search

The literature search was conducted using the APA PsychInfo database. A search for peer-reviewed articles with the keywords «MBI-GS», «MBI», «factor analysis», «factor structure», «factorial validity», «construct validity», «measurement invariance», and «multigroup analysis» resulted in 504 articles. Of these, 94 were duplicates, 108 did not report item-level data (e.g., factor loadings), 68 were not applicable (i.e., they included the MBI or MBI-GS but did not examine factorial validity), and 11 were literature review articles, which were excluded. The final sample included 223 articles.

Data coding

The content analysis was carried out by five researchers, including the study authors and three well-trained PhD students. To assess consistency in data coding, a random subsample of 15 articles was independently analyzed by all five researchers. The mean Cohen's kappa coefficient across the different variables was .93, indicating almost perfect agreement between raters.

Evaluation by experts

To ensure the selected items adequately represented the construct, content-domain evaluations were performed by expert judges following recommendations by Smith et al. (2000). Four Argentine researchers were invited to participate via email by the first author. These experts were selected for their experience in organizational research and familiarity with the construct under study. Two of the researchers also had significant experience in constructing and validating psychological tests. Each expert received a document via email containing the following components, presented in the same order: (1) detailed information on the conceptualization of the target construct; (2) the response format; (3) scale instructions; and (4) the items. Experts were asked to independently assess whether the items were representative of each construct and whether the content domain of each construct was adequately covered by the items. In other words, they evaluated whether the breadth of the construct was faithfully represented by the selected sample of items. Experts rated their agreement using a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). They were also encouraged to provide suggestions or comments regarding the items' content. All four experts were blinded to each other's identities and responses throughout the data collection process.

Data analysis

Aiken's V coefficient was used to quantify the agreement among experts regarding the quality of the items and to assess content validity. The V coefficient ranges from 0 to 1, with higher values indicating stronger content validity. Aiken (1985) suggests that a V value of at least .50 is acceptable for content validity, but in this study, we used a more conservative criterion of V > .70 for item retention. In addition, to provide a more rigorous null hypothesis testing of the V value in the population (V_p), confidence intervals (CIs) were also calculated using a Visual Basic computer program (Merino & Livia, 2009). The 90% confidence intervals were estimated, as recommended when the number of expert judges is small (Merino & Livia, 2009), as in this study. Items with a null value of V_0 = .70 within the 90% CI were removed from the scale, while items were retained if the lower limit of the CI exceeded V_0 = .70.

Results

A total of 16 items were initially selected, with four items representing each of the burnout dimensions: exhaustion, cynicism, depersonalization, and professional inefficacy. These items were chosen based on their highest average factor loadings on their respective factors (mean λ ranging from .68 to .75). During the analysis, Correlated residuals for two items were consistently identified across different studies, and two other items were found to be non-invariant across studies. As a result, these four items were removed from further consideration. Detailed results of this analysis are available upon request from the corresponding author. After removing these items, a 12-item draft version of the SBM was created and submitted to experts for evaluation. Given our primary goal of developing a brief scale with two measurement indicators per factor, expert ratings were used to identify the items that best represented each content domain, as indicated by the highest Aiken's V coefficient.

Descriptive statistics and Aiken's V coefficient for the selected items are presented in Table 2. As shown in the table, all items met the inclusion criterion, with the lower bound of the confidence intervals exceeding .70. Notably, experts suggested minor adjustments to some items, such as changes in wording or phrasing. These adjustments were made to enhance clarity and precision without altering the intended meaning of the items (see Table 2).

Table 2

Summary of expert ratings on the content validity of the Short Burnout Measure

Items	Min	Max	Mean	Aiken's V	90% IC	
					Lower bound	Upper bound
1. I feel less and less connected to my job [a]	4	5	4.75	.93	.76	.98
2. I do not have a clear idea of the value and purpose of my job [a]	5	5	5	1	.86	1
3. I am harsher and less sympathetic with people than perhaps they deserve [a]	4	5	4.75	.93	.76	.98
4. I am worried this job is making me emotionally harsher [a]	5	5	5	1	.86	1
5. I find it difficult to relax after a workday	5	5	5	1	.86	1
6. After a day of work, I feel run-down and drained of physical or emotional energy [a]	4	5	4.75	.93	.76	.98
7. I feel that I am achieving less than I should	4	5	4.75	.93	.76	.98
8. In my opinion, I'm inefficient in my job [b]	5	5	5	1	.86	1

Note. Statistics based on ratings of four expert judges using a 5-point Likert response scale were 1 = *strongly disagree*, 5 = *strongly agree*. Min = lowest rating provided by an expert on each item; Max = highest rating provided by an expert on each item[a] These items were adapted versions of the original scale based on experts' suggestions[b] Schaufeli, W. B., & Salanova, M. (2007). Efficacy or inefficacy, that's the question: Burnout and work engagement, and their relationships with efficacy beliefs. Anxiety, stress, and coping, 20(2), 177-196. Reprinted by permission of Taylor & Francis Ltd, http://www.tandfonline.com

Part 2. Validity and reliability of the SBM

Method

Design

An empirical instrumental study (Montero & León, 2007) using a cross-sectional design was conducted. Instrumental studies involve the development of new psychological tests, and the evaluation of their psychometric properties. Factorial validity was evaluated using confirmatory factor analysis (CFA). Based on our four-dimensional conceptualization of burnout, we hypothesized four interrelated but distinct factors: exhaustion, cynicism, depersonalization, and professional inefficacy. Next, we assessed the reliability of the SBM by examining the construct reliability of each subscale. We also tested the criterion validity of the SBM by exploring its associations with turnover intention and the employee Net Promoter Score (eNPS). Past research has consistently shown a positive association between burnout and turnover intention (Russell et al., 2020; Swider & Zimmerman, 2010). Hence, a positive relation is expected between SBM scores and turnover intention. The eNPS assesses the likelihood of employees recommending their company as a workplace (Yaneva, 2018). As burnout negatively influences employees' perceptions of their workplace (Guan, 2021), we anticipated a negative relationship between SBM scores and eNPS.

Participants

A total of 1256 workers from the Information Technology (IT) sector in Argentina participated in the study. The only eligibility criterion was being currently employed. The sample consisted of 56.1% males, with participants' ages ranging from 18 to 59 years (M = 25.16, SD = 6.71). Forty-eight percent held managerial positions, and 52% were team members. Recruitment was conducted via a web-based survey distributed through various channels, including social media (Twitter®, LinkedIn®) and tech industry-related portals (e.g., News.ycombinator, Fast Company).

Measures

Burnout

The SBM includes eight items assessing four dimensions of burnout: exhaustion, cynicism, depersonalization, and professional inefficacy. Table 2 presents the scale items. Items 1, 3, and 4 were adapted from the MBI-GS (Schaufeli et al., 1996), while items 2, 5, and 6 were adapted from the original MBI (Maslach & Jackson, 1981). Items 7 and 8 were sourced from studies by Simbula and Guglielmi (2010) and Schaufeli and Salanova (2007), respectively. Participants rated their feelings about their current job over the past few weeks on a 7-point scale, ranging from 0 (*never*) to 6 (*every day*).

Employee Net Promoter Score (eNPS)

The eNPS measures the likelihood that employees would recommend their company as a place to work. It is based on the Net Promoter Score (NPS), a widely utilized metric in marketing research for assessing customers' propensity to recommend a company's products or services to others (Reichheld, 2003). In this study, eNPS was measured using a single-item scale from Yaneva (2018): «How likely are you to recommend your company to a friend or colleague as a place to work?» Responses were given on a scale ranging from 0 (*not at all likely*) to 10 (*extremely likely*), with higher scores indicating a greater likelihood of employees recommending their company. The validity of the single-item eNPS scale has been supported by significant correlations with measures of employee satisfaction and engagement (Yaneva, 2018). In addition, research in the marketing domain has demonstrated the reliability as well as the nomological, concurrent, and predictive validity of single-item measures of NPS (Pollack & Alexandrov, 2013). Although formal psychometric validation of the eNPS in Argentina is currently lacking, it is increasingly used in organizational research and practice throughout Latin America (Rankmi, 2023).

Turnover intention

Turnover intention was assessed using a 4-item scale from Houkes et al. (2001). An example item is: «Within the next six months, I'll be out of this company». Participants responded on a 5-point Likert scale, ranging from 1 (*very unlikely*) to 5 (*very likely*). Confirmatory factor analysis was conducted on the current sample using the WLSMV estimator and polychoric correlations. The results supported the unidimensionality of the scale, as evidenced by excellent fit indices: CFI = .97, TLI = .96, RMSEA = .059 (90% CI [.053, .065]), WRMR = .89. The reliability coefficient (Cronbach's alpha) for the present sample was .81. A total composite score for each participant was computed by summing the item scores, with higher scores indicating stronger turnover intention.

Procedure

Participants completed an online survey that included the SBM, turnover intention, and eNPS measures. The survey was administered sequentially, with each item presented individually –starting with the SBM items, followed by questions on turnover intention, eNPS, and sociodemographic information. On average, completion took between two and four minutes. Participants were required to complete all items before submitting the survey, ensuring that no missing data was recorded. This study adhered to the ethical principles outlined in the Declaration of

Helsinki and was approved by the Bioethics Committee of the Universidad Católica de Córdoba (Reference Number: 0324, March 7, 2024). Participation was entirely voluntary. All participants provided informed consent after receiving an information sheet that clearly described the study's aims and procedures, the confidentiality and anonymity of responses, and their right to withdraw at any time without providing a reason. A contact email address was also provided for participants seeking additional information or clarification. No compensation or incentives were offered for participation.

Data Analysis

Confirmatory factor analysis was used to examine factorial validity. Several measurement models were tested and compared to determine which provides the best fit for the data. Model 1 (M1) assumes a single latent burnout factor. Model 2 (M2) is a three-factor model consisting of exhaustion, «mental distancing» (including cynicism and depersonalization items), and professional inefficacy. Model 3 (M3) is an alternative three-factor model, including exhaustion, depersonalization, and a third factor that combines cynicism and professional inefficacy into a single factor, based on their high latent factor correlation (see Table 4). Given that any correlation of $|r| \geq .80$ is considered a signal of redundancy (Ferrando & Morales-Vives, 2023), this model was tested to assess possible lack of discrimination. Model 4 (M4) assumes four correlated but distinct factors: exhaustion, cynicism, depersonalization, and professional inefficacy. Models 5 (M5) and 6 (M6) are higher-order and bifactor models, respectively. All models were estimated using Mplus 7.11 with the robust weighted least squares (WLSMV), an asymptotically distribution-free estimator based on the polychoric correlation matrix, specifically designed for ordinal data (Li, 2016). Given the well-known oversensitivity of the chi-square test to sample size and minor misspecifications (Marsh et al., 2005), various fit indices were calculated to assess model fit: the root mean square error of approximation (RMSEA) with its 90% confidence interval (CI), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the weighted root-mean-square residual (WRMR). Typically, CFI and TLI values exceeding .90 and .95, respectively, indicate good and excellent fit to the data, while RMSEA values below .08 and .06 suggest good and excellent model fit, respectively (Browne & Cudeck, 1993; Hu & Bentler, 1998). Moreover, the upper limit of the 90% RMSEA confidence interval (CI) should not exceed .10 (Kline, 2023). For WRMR, values below 1.00 are indicative of good model fit (DiStefano et al., 2018). Model comparisons were based on RMSEA 90% confidence intervals and changes in TLI (ΔTLI; Gignac, 2016; Marsh et al., 2005). Significant differences in model fit were indicated by non-overlapping RMSEA 90% CIs and $\Delta TLI \geq .01$ (Marsh et al., 2005; Wang & Russell, 2005). It is important to note that these cut-off values serve as rough guidelines; therefore, a comprehensive assessment of model parameters was carried out considering their statistical plausibility and theoretical adequacy (Morin et al., 2016).

Construct reliability for each SBM factor was assessed using the *H* index, calculated with a freely available Microsoft Excel-based calculator (Dueber, 2017). The *H* coefficient indicates how well a set of items represents a latent construct. A value greater than .70 typically indicates good reliability (Hancock & Mueller, 2001). Bivariate Pearson correlations were computed between SBM factor scores and eNPS and turnover intention scores using SPSS 20.0.

Results

Goodness-of-fit-statistics for all measurement models are presented in Table 3. As shown in the Table, Model 1 revealed poor fit to the data, as indicated by all fit indices failing to meet the recommended guidelines, except for CFI. Model 2 and Model 3 showed improved model fit indices, with CFI and TLI > .95 and WRMR < 1.00. However, RMSEA was still elevated (> .08, and the upper limit of 90% IC exceeding .10). In contrast, Model 4, which corresponds to the four-factor model, demonstrated excellent fit (CFI and TLI > .95, RMSEA < .06, WRMR < 1.00), and was superior to the other models, as indicated by ΔTLI ≥ .036 and non-overlapping RMSEA 90% CIs.

Table 3

Goodness-of-fit indices for the different CFA models

Model	Description	χ^2	df	CFI	TLI	RMSEA (90% CI)	WRMR
M1	One-dimensional model	661.90***	20	.90	.86	.226 (.211, .241)	2.22
M2	Three-correlated model	183.55***	17	.97	.95	.125 (.109, .142)	1.05
M3	Alternative three-correlated model	173.18***	17	.98	.96	.121 (.105, .138)	.98
M4	Four-correlated model	26.60*	14	.998	.996	.038 (.014, .060)	.33
M5	Higher-order model	70.07***	16	.992	.985	.073 (.056, .091)	.61
M6	Bifactor model [a]	271.99*	17	.96	.93	.155 (.139, .171)	1.32

Note. CFA: confirmatory factor analysis, χ^2 = chi-square test of model fit, df = degree of freedom, CFI = comparative fit index, TLI = Tucker-Lewis index, RMSEA = root mean square error of approximation, IC = confidence interval, WRMR = weighted root means square residual. [a] This model revealed out-of-range parameter estimates (i.e., a factor loading greater than 1) and should therefore be interpreted with caution or dismissed.

*** $p < .001$, * $p < .05$

A detailed examination of the parameters estimates from the four-factor model revealed substantial correlations between exhaustion, cynicism, depersonalization, and professional inefficacy (Table 4), suggesting potential overlap. To address this issue, we compared the average variance extracted (AVE) for each factor with the shared variance (ϕ) between all pairwise factor combinations. Discriminant validity is supported if the AVE for two constructs exceeds their shared variance (Farrell, 2010). The AVE for each factor (exhaustion .69, cynicism .71, depersonalization .65, and professional inefficacy .55) was higher than the shared variance (ϕ ranging from .29 to .49). These results suggest that, despite their strong intercorrelations, exhaustion, cynicism, depersonalization, and professional inefficacy, as measured by the SBM, are distinct dimensions, further supporting the CFA findings.

Next, we tested a higher-order model (M5) in which exhaustion, cynicism, depersonalization, and professional inefficacy were modeled as first-order factors, with a second-order burnout factor influencing the items through the first-order factors. As shown in Table 3, this model demonstrated adequate fit to the data, with all fit statistics meeting or exceeding the specified guidelines. However, the four-factor model provided a better fit, as evidenced by non-overlapping RMSEA 90% CIs and ΔTLI = .011. Finally, we tested a bifactor model (M6) consisting of a general burnout factor and four specific factors (exhaustion, cynicism, depersonalization and professional inefficacy) was tested. All factors directly influenced the items and were modeled as orthogonal, in line with bifactor assumptions (Pekmezci, 2022). Results show acceptable fit indices for the CFI, TLI but not for the WRMR and RMSEA. Additionally, the bifactor model yielded anomalous parameter estimates (i.e., a factor loading greater than 1), making it statistically improper. In conclusion, based on overall fit indices and a detailed assessment of all parameter estimates, the four-factor model provides the best representation of the underlying SBM factor structure and was retained for subsequent analysis. The complete standardized factor loadings for this model are presented in Table 4.

Table 4
Standardized factor loadings (top) and latent correlations (bottom) for the four-factor model

	Exhaustion	Cynicism	Depersonalization	Professional inefficacy
I find it difficult to relax after a workday	.81			
After a day of work, I feel run-down and drained of physical or emotional energy	.92			
I feel less and less connected to my job		.90		
I do not have a clear idea of the value and purpose of my job		.82		
I am harsher and less sympathetic with people than perhaps they deserve			.75	
I am worried this job is making me harsher emotionally			.82	
I feel that I am achieving less than I should				.87
In my opinion, I'm inefficient in my job				.82
Exhaustion	–	.66***	.74***	.63***
Cynicism		–	.78***	.81***
Depersonalization			–	.58 ***
Professional Inefficacy				–

*** p < .001

Reliability

The results indicate good construct reliability for all SBM factors: exhaustion (.88), cynicism (.86), depersonalization (.77), and professional inefficacy (.84).

Criterion-related validity

The associations between SBM factors, turnover intention, and eNPS are presented in Table 5. As expected, higher levels of exhaustion, cynicism, depersonalization, and professional inefficacy were associated with greater turnover intention and lower eNPS scores.

Table 5
Intercorrelations among SBM dimensions, turnover intention, and eNPS

	1	2	3	4	5	6
1. SBM-Exhaustion	–					
2. SBM-Cynicism	.49***	–				
3. SBM-Depersonalization	.51***	.58***	–			
4. SBM-Professional inefficacy	.46***	.65***	.49***	–		
5. Turnover intention	.30***	.55***	.41***	.41***	–	
6. Employee net promoter score (eNPS)	-.26***	-.46***	-.41***	-.29***	-.53***	–

*** p < .001

Discussion

The high prevalence of burnout among workers has become a significant societal concern in the 21st century, particularly since the global COVID-19 pandemic, which has negatively impacted the mental health of workers (Kumaresan et al., 2022; Nagarajan et al., 2024). Sharma et al. (2020) emphasized the need for novel and innovative measures to assess burnout both during the COVID-19 pandemic and in the post-COVID era, to evaluate how workers adapt to challenges in changing working conditions. The present study addressed this issue by developing a new scale.

The findings from CFA supported a four-factor model for the SBM, consistent with our initial conceptualization of burnout. These factors included exhaustion, cynicism, depersonalization, and professional inefficacy. Although these factors showed strong associations, comparison between the average variance extracted (AVE) and shared variance indicated that they are empirically distinct constructs. Additionally, a higher-order model demonstrated good fit to the data, suggesting that the SBM subscales assess a common overarching construct. Thus, computing a total SBM scale score for measuring overall burnout appears to be appropriate. However, our findings indicate a superior fit of the four-factor model compared to the higher-order model, indicating that each burnout dimension should be evaluated and scored independently for a more accurate assessment.

From a practical standpoint, using four separate subscale scores may be more advantageous than using a total scale score, as it provides a more detailed assessment of burnout symptoms. Recent research (Morera et al., 2020) has distinguished between different burnout subtypes or profiles (e.g., burned-out, overextended/strain, disengaged/cynical, ineffective) based on scores across various burnout dimensions. Moreover, certain profiles, such as overextended or disengaged, are considered early warning signs of a later, more complete burnout experience. By examining each dimension independently, a more nuanced assessment becomes feasible. This approach facilitates identifying phases in the progression of burnout, enabling targeted interventions for each phase.

In agreement with past research (Salanova et al., 2005; Simbula & Guglielmi, 2010) our results show that cynicism and depersonalization are distinct constructs that should be measured independently. Using separate scales for cynicism and depersonalization has significant practical implications. For instance, it allows for the examination of whether employees are highly depersonalized in their relations with coworkers, customers, or clients, whether they have higher levels of cynicism about their job, or both. Each situation may have different consequences for employees and organizations, requiring distinct intervention strategies (Simbula & Guglielmi, 2010). On the other hand, our results support previous studies (Bresó et al., 2007; Maroco et al., 2014; Morgan et al., 2014) that advocate for the inclusion of professional inefficacy as a constituent dimension of burnout, alongside exhaustion, cynicism, and depersonalization.

Reliability analyses showed good construct reliability for all SBM factors. Finally, as expected, the SBM dimensions were positively correlated with turnover intention and negatively with ePNS, providing additional support for the validity of the scale. In summary, the findings of the present study demonstrate satisfactory psychometric properties for the SBM in terms of content validity, factorial validity, construct reliability, and criterion-related validity.

Implications for research and practice

Four key implications emerge from the findings of the current research. First, the inclusion of separate scales for cynicism and depersonalization offers a more comprehensive and fine-grained assessment of the mental distancing component of burnout. Second, the genuine inefficacy scale in the SBM provides a more appropriate operationalization compared to the commonly used MBI/MBI-GS self-efficacy scale with reversed items, in line with previous recommendations (Schaufeli & Salanova, 2007). By avoiding the undesirable psychometric problems of reversed items (see Vigil-Colet et al., 2020), the SBM can be used to improve our understanding of the inefficacy dimension and help clarifying the ongoing debate about its role in burnout. Third, the SBM represents a validated, brief measurement tool that organizational psychologists and human resources practitioners can use to quickly assess burnout levels in employees across various timeframes (e.g., daily, weekly, or during weekends) and evaluate the effectiveness of burnout-reduction interventions. Fourth, the SBM's brevity offers significant practical advantages for research. It can be used alongside other measures to examine associations between burnout and multiple constructs, such as in SEM models including different antecedents and/or consequences of burnout. The SBM may also be useful in repeated-measure designs or day-level studies examining intra-individual fluctuations in burnout throughout the workday, allowing participants to complete the scale multiple times per day without experiencing fatigue or boredom often associated with longer scales.

Limitations and suggestions for future research

There are several limitations of the present study that should be acknowledged. First, although expert ratings suggest that the SBM items adequately cover the content domain, additional research is needed to determine whether the items fully capture the heterogeneity of the burnout construct. Investigating the correlations between the SBM and other theoretically similar but longer measures of burnout (e.g., MBI-GS) would shed light on this issue. Second, despite the utilization of a large sample, participants were exclusively IT workers from Argentina. Consequently, caution should be taken when generalizing the results to other occupational groups or countries. Further research is needed to replicate these results and establish the validity and reliability of the SBM across diverse occupations and countries.

Second, although the study included a large sample, all participants were exclusively IT workers from Argentina. Therefore, the findings should not be generalized to other occupational contexts or countries. The characteristics of the IT sector –such as high cognitive demands, remote work culture, and rapid technological changes (Beer & Mulder, 2020)– may limit the applicability of the results to other professions. Future studies are strongly encouraged to replicate and extend these findings using samples from different occupational sectors and cultural settings in order to further establish the generalizability, validity, and reliability of the SBM.

Third, we used internet-based method for collecting data. Although previous studies have shown comparable psychometric properties between online and paper-and-pencil questionnaires (Quijada et al., 2023; Zeiler et al., 2020), replication studies using a paper-and-pencil version of the scale would be beneficial to confirm the robustness of the SBM across different data collection methods. Fourth, our results support the validity of the inefficacy scale and, in line with previous research (Maroco et al., 2014; Morgan et al., 2014), we recommend using a self-inefficacy scale rather than a reversed self-efficacy scale. However, as Schaufeli and Salanova (2007) noted, «efficacy and inefficacy are more likely to be strongly (but not perfectly) and negatively related to each other» (p. 179). This suggests that while efficacy and inefficacy are related, they are distinct constructs with different correlates and consequences. For instance, low scores on efficacy suggest that an individual feels less capable of managing job stressors but may not feel entirely incapable, potentially leading to different outcomes (e.g., to experience job strain or withdrawal). This distinction mirrors the structure of affect, where low scores on negative affect is not equivalent to high scores on positive affect, and vice versa (Flores-Kanter et al., 2021). Therefore, future research could explore whether efficacy and inefficacy are differently related to antecedents and outcomes. Such studies will not only provide further evidence on the construct validity of the inefficacy scale, but also elucidate whether an inefficacy scale could provide additional valuable information to the efficacy scale.

Finally, future studies should investigate additional psychometric properties of the SBM, such as test-retest reliability and convergent, discriminant, and incremental validity with other established burnout measures. This will provide further support for the validity and usefulness of the SBM.

Time constraints in organizational research often limit the use of lengthy measures, especially in complex research designs involving multiple constructs (Maloney et al., 2011). Using full versions of all measures in such a design may not be feasible, which confronts researchers with a dilemma: reduce the number of constructs or shorten the length of the measures. The present study developed a brief burnout measure based on existing scales through a strategic item selection process. This approach minimizes threats to validity and reliability by selecting the most effective measurement indicators. The inclusion of separate scales for cynicism and depersonalization, as well as the assessment of the inefficacy dimension using a genuine inefficacy scale, represent two key advantages of the newly developed measure over existing burnout scales. By providing a comprehensive, valid, and reliable assessment of burnout without the drawbacks of longer measures, the SBM allows researchers to conduct studies within the constraints of time and resources.

Conflict of interest

No potential conflict of interest was reported by the authors.

Ethical declaration

This study was approved by the Bioethics Board of the Bioethics Committee of the Universidad Católica de Córdoba (Reference Number: 0324).

Authorship contribution

CLS: Conceptualization, investigation, funding acquisition, project administration, writing –original draft, writing– review and editing.

MAT: Data curation, methodology, software, writing –original draft; writing– review and editing.

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