

Measuring work-life wellness: A South African validation study

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Orientation: The COVID-19 pandemic accelerated the shift towards flexible work arrangements, highlighting concerns about work-life balance and employee well-being. To address these issues, a reliable and validated measurement instrument to measure work-life wellness in South African workplaces is essential.

Research purpose: The study's main aim was to validate and assess the dimensionality of the Work-Life Wellness Scale (WLWS), developed by Como and Domene (2022), within the South African context. We also tested for approximate invariance of the measure for age groups.

Motivation for the study: Limited research exists on the construct of work-life wellness (WLW), and no validated instrument is available to measure this concept in South Africa. Validating and providing empirical support for the dimensionality of the WLWS will provide researchers and practitioners with a psychometrically sound instrument for assessing WLW effectively. Approximate measurement invariance is a prerequisite for studying differences between age groups.

Research approach/design and method: A quantitative, cross-sectional survey design was employed, obtaining 323 completed responses from full-time employees of a South African retail organisation. Statistical analyses included descriptive statistics, confirmatory factor analysis, bifactor model analysis and measurement invariance across age groups.

Main findings: A bifactor model analysis revealed that the WLWS is essentially unidimensional, with a dominant general work-life wellness factor. While items related to work-life functioning (WLF) and work-life interference (WLI) are included, they primarily reflect this overarching construct. Measurement invariance testing largely supported configural, metric and scalar invariance across age groups.

Practical/managerial implications: The findings offer guidance for using the WLWS in practice, emphasising the interpretation of the overall WLW score. Organisations can use this validated tool to assess employee work-life wellness and develop targeted interventions to improve well-being.

Contribution/value-add: This study adds value by providing an instrument for assessing WLW in South Africa, contributing to local employee wellness research and informing culturally relevant HR policies and practices.

Keywords: Work-Life Wellness; Work-Life Wellness Scale; Reliability and Validity; Bifactor Modelling; Employee Well-Being; South Africa

Introduction and background

Employee wellness, defined as the overall state of an employee's physical, mental and emotional well-being in the workplace, is a significant concern for employers because of its direct impact on productivity, absenteeism, retention and overall organisational performance (Bhatasana, n. d.; Trivella, 2023). Although employee wellness was an important issue before the Coronavirus Disease 2019 (COVID-19), the pandemic has significantly affected employee well-being in South African organisations. It has necessitated a transition to remote work and heightened the emphasis on supporting employees' overall well-being (Botha & Coetzee, 2022; Fatima et al., 2022). Research indicates that work-from-home arrangements have led to challenges such as increased workloads, stress, burnout and loneliness at home (Botha & Coetzee, 2022; Du Plessis, 2022; Terry, 2024). A significant challenge of working from home is maintaining a healthy work-life balance and, consequently, work-life wellness. Work-life wellness is understood as the equilibrium achieved between one's professional and personal

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life, facilitated through various methodologies such as integration, balance and segmentation (Como et al., 2021). It thus represents a state of harmony between work and life.

Como and Domene (2022) acknowledged the need to enhance work-life wellness in the contemporary workplace, leading to the development of the Work-Life Wellness Scale (WLWS), a 10-item measure focusing on two key areas: work-life functioning (WLF) and work-life interference (WLI). While the scale has demonstrated internal consistency ($\alpha = 0.90$) within a Canadian sample, its psychometric properties remain untested in other contexts. Given the limited literature on the WLW construct and Como and Domene's (2022) recommendation to validate the scale across diverse samples, this study first aims to establish the construct validity of the WLWS within a South African context. It furthermore responds to Como and Domene's (2022) call for further research on the structure of the work-life wellness construct. While these authors theorised that the WLWS measures two psychometrically distinct factors (WLF and WLI), they recommended using the full scale, stating that there was no empirical evidence to measure WLF and WLI as independent subscales. The dimensionality of the WLWS was consequently empirically assessed to determine whether it should be regarded as a unidimensional or multidimensional construct.

Questionnaire validation is crucial to ensure the accuracy and reliability of instruments measuring latent variables or constructs (Zhang & Aryadoust, 2022). This process involves multiple interrelated tests to establish validity, reliability and responsiveness (Carvalho et al., 2020). Validating questionnaires in South Africa is crucial for ensuring cultural relevance, accurate translation and psychometric integrity (Laher & Cockcroft, 2013). Adapting instruments to local norms and values maintains their reliability and validity, leading to more effective interventions and equitable research outcomes. This process supports culturally sensitive policies and enhances the credibility of research.

Validating wellness scales in South Africa is crucial for ensuring that measures of psychological well-being are culturally and psychometrically appropriate. Studies on scales such as the Flourishing-at-Work Scale (Short Form) (FWS-SF) (Rautenbach & Rothmann, 2017), the Meaning in Life Questionnaire (MLQ) (Temane et al., 2014) and others have shown varied results, with some scales needing further adaptation for the South African context. Challenges such as language translation, cultural sensitivity and emic-African perspectives (Diessel, 2007; Mhlongo et al., 2022) must be addressed. Effective validation supports accurate assessment across diverse populations and enhances the utility of scales in clinical, community and work settings (Laher & Cockcroft, 2013).

Evaluating the dimensionality of a measurement scale is crucial for accurately capturing the underlying construct.

This evaluation is essential for understanding the data's structure and ensuring the validity and reliability of the measurement tool (Lutz et al., 2021; Markos & Tsigilis, 2024). While Como and Domene (2022) acknowledge the existence of two highly interrelated dimensions of WLW (WLF and WLI), they suggest a unidimensional structure for the WLWS because WLW and WLI measure complementary aspects of the WLW construct. However, treating substantively multidimensional constructs as unidimensional can lead to biased item parameter estimates, loss of information and, ultimately, incorrect conclusions (Garrido et al., 2019). An assessment of the dimensionality of the WLWS is thus necessary.

Work-life wellness (WLW) typically varies across age groups because of factors such as lifestyle, emotional regulation and job characteristics. Research shows that younger employees often experience higher stress and poorer lifestyle choices, leading to lower WLW (Lucini et al., 2023). In contrast, older workers often report higher life satisfaction and better work-life balance, increasing WLW (Choi et al., 2024). These differences necessitated testing the WLWS for measurement invariance across age groups to ensure that it reliably measures WLW for all ages, enabling meaningful comparisons and guiding the development of targeted age-specific workplace wellness programmes.

Given this background, this study aims to assess the validity and reliability of the WLWS, developed by Como and Domene (2022), within the South African context. Validating this scale will equip South African researchers with a reliable measure that accurately captures the country's unique cultural, social and economic contexts, thereby advancing local employee wellness research. The study further aims to empirically assess the scale's dimensionality and test for measurement invariance across different age groups. This study makes a theoretical contribution by operationalising the WLW construct in South Africa, enabling further research into the antecedents of employee well-being and informing strategies to enhance it.

Literature review

In today's competitive business landscape, organisations increasingly recognise the importance of employee well-being for sustainable success. Mounting evidence shows a direct relationship between employee well-being and organisational performance, prompting a shift in HRM practices (Mahdia, 2024). This shift involves a dedicated effort to create and maintain a supportive work environment that improves employees' health and well-being. Consequently, human resource management and industrial and organisational practitioners are vital in implementing initiatives that enhance employees' health, happiness and productivity (Gupta et al., 2024).

The pandemic, which prompted a widespread shift to remote work, has significantly impacted employee well-being

(Du Plessis, 2022) and, by extension, work-life wellness (Como & Domene, 2022). Work-life wellness (WLW) is a relatively new concept in academic literature, referring to the positive interaction between work and personal life without requiring perfect balance or integration (Como et al., 2020). Work-life wellness is defined as the ability to thrive across various life domains while feeling satisfied with the interplay between work and personal life (Como & Domene, 2022). This concept differs from work-life balance, which focuses on managing time between work and personal life according to individual preferences (Haar et al., 2019), and from work interaction with personal life, which examines how work can either enhance or interfere with personal life (Fisher et al., 2009).

Optimal work-life wellness enables individuals to effectively manage various demands from both work and personal life, such as taking vacation days to accommodate family needs. Work-life interference occurs when work responsibilities overshadow personal obligations, potentially diminishing overall wellness (e.g., working late to finish a project). While balancing work and personal life is crucial for job performance and personal success, true work-life wellness goes beyond mere balance (Como & Domene, 2022). It encompasses feeling optimistic about both aspects of life, such as enjoying one's job and having time to pursue other interests, as well as maintaining a harmonious connection between work and personal life (e.g., having a supportive job with minimal disruptions to personal time).

Como and Domene (2022) theoretically conceptualise work-life wellness as a multi-dimensional construct, encompassing both work-life functioning (the trade-off between work and personal life) and work-life interference (instances where work demands overshadow personal needs). This perspective views work-life wellness as harmony achieved through integration, balance and segmentation (Como et al., 2021). Although the concept is new and the literature is scarce, understanding and supporting work-life wellness is essential for enhancing employees' physical and mental health and productivity (Como & Domene, 2022). Consequently, for this study, the questionnaire developed by Como and Domene (2022) was explicitly validated within the South African context, responding to the authors' call for further research in different settings to confirm the construct validity of the instrument.

The work-life wellness scale (WLWS) is a 10-item tool designed by Como and Domene (2022) to assess work-life wellness by focusing on two primary domains: work-life functioning (WLF) and work-life interference (WLI). Work-life functioning encompasses aspects of work-life balance and the enhancement of personal life, while work-life interference addresses how work can negatively affect one's personal life. The scale was developed by integrating items from three validated scales. Initially comprising 11 items across three domains — work-life balance (4 items), work interference with personal life (5 items), and work

enhancement of personal life (2 items) — one item was excluded after factor analysis because of weak factor loading, resulting in the final 10-item version. Participants rated each item on a 7-point Likert scale, ranging from strongly disagree (1) to strongly agree (7), with higher scores reflecting better self-rated work-life wellness. The scale demonstrated strong internal consistency, with a Cronbach's alpha of 0.90 (Como & Domene, 2022). While the WLWS consists of two psychometrically distinct factors (WLF and WLI), Como and Domene (2022) emphasise that these factors represent complementary aspects of work-life wellness rather than independent subscales. Given the lack of sufficient evidence to treat WLF and WLI separately, the authors recommend using the full-scale score to capture overall work-life wellness. However, the dimensionality of the WLWS has not been empirically confirmed in subsequent studies. The present study empirically examines whether the scale should be treated as a unidimensional or multidimensional construct to address this gap. By thoroughly assessing the scale's factor structure, this study aims to determine whether WLF and WLI should be considered distinct but related dimensions or whether the scale functions as a single overarching measure of work-life wellness. According to Zanon et al. (2021), clarifying the dimensionality of a scale will enhance its validity and improve its applicability in research and practice.

Questionnaire validation is crucial in South Africa because culturally and contextually relevant tools are essential for accurately assessing and understanding wellness among diverse populations (Stockton et al., 2024). Over the past decade, only a few wellness questionnaires have been validated in South Africa, which has resulted in lack of reliable instruments for measuring well-being within the country. For instance, Cromhout et al. (2022) investigated the Questionnaire for Eudaimonic Well-Being (QEWB), finding support for a bifactor structure in student samples but a poor fit in adults, suggesting that the measurement of EWB may differ across developmental phases. Mpondo et al. (2021) validated several psychological well-being (PWB) measures — hope, faith, social support, self-efficacy and life satisfaction — for use in South Africa. These measures demonstrated unidimensional factor structures, good model fit indices and high internal consistency. Additionally, they showed moderate to good test-retest reliability, with minor practice effects. Similarly, Nel et al. (2019) validated the Experience of Work and Life Circumstances Questionnaire (WLQ), confirming its unidimensional structure and strong fit among employees in the financial and health sectors. Du Plessis and Guse (2017) evaluated the Scale of Positive and Negative Experiences (SPANES) in university students, finding generally good Rasch fit and reliability, with minor issues in two items. These validated instruments, however, tend to focus only on certain wellness aspects while overlooking the broader concept of work-life wellness. Therefore, this research aims to address a critical gap in the literature by examining the psychometric properties of the WLWS, which is crucial for its practical application in

South African workplaces. By doing so, the study contributes to the academic field and provides practitioners with a valid and reliable tool for assessing wellness in a culturally and contextually appropriate way for the diverse South African population.

Materials and method

Research approach and design

A quantitative research approach was used for this study, focusing on numerical data and statistical analysis for objective measurement and comparison (Saunders et al., 2023). Specifically, a cross-sectional survey design was employed. Cross-sectional designs collect data from a sample at a single point in time (Leavy, 2022), while surveys provide a quantitative overview of trends, attitudes and relationships between variables within a population through a representative sample (Creswell & Creswell, 2022). This approach offers a structured and efficient way to evaluate the reliability and validity of a research instrument.

Research participants

The survey was administered to full-time employees of a retail organisation that had initiated a wellness programme following the COVID-19 pandemic. While the invitation to participate in the study was extended to all 1829 full-time employees, only those who had previously participated in organisational wellness programmes were eligible. This resulted in a purposive sample of 323 fully completed questionnaires. The purposive sampling strategy, which required an element of self-selection, allowed the researchers to collect data directly pertinent to the research objectives (Bell et al., 2022). Of the participants, 190 were female (58.82%) and 130 male (40.25%), with 3 individuals (0.93%) opting not to disclose their gender. The majority of the participants were aged between 21 and 30 years (9.91%), followed by those in the 31 to 40 years (36.84%) and 41 to 50 years (33.75%) age groups. In terms of education, the largest portion of participants held a Bachelor's Degree or Advanced Diploma (24.46%), followed by those with a Grade 12 Certificate (17.65%) or Diploma or Advanced Certificate (17.65%).

Measuring instrument

The Work-Life Wellness Scale (WLWS), developed by Como and Domene (2022), was administered to measure work-life wellness. The scale is a 10-item tool designed to measure work-life wellness in two domains: work-life functioning (WLF) and work-life interference (WLI). Participants were required to rate each item on a 7-point Likert scale, with higher scores indicating better work-life wellness. As mentioned, the scale demonstrated strong internal consistency (Como & Domene, 2022).

Demographic information, such as age, gender and highest level of education, was also collected to describe the respondents' characteristics.

Research procedure

The self-administered questionnaire was uploaded in English onto the Qualtrics online platform, which generated a unique URL. This URL and a participant information sheet were included in an email sent to an identified gatekeeper within the organisation. The gatekeeper then distributed the invitation to participate and the questionnaire link to all 1829 full-time employees, inviting those who completed the organisational wellness programmes to participate in the study. Upon accessing the link, participants were directed to the online platform, where their responses were collected anonymously.

Statistical analysis

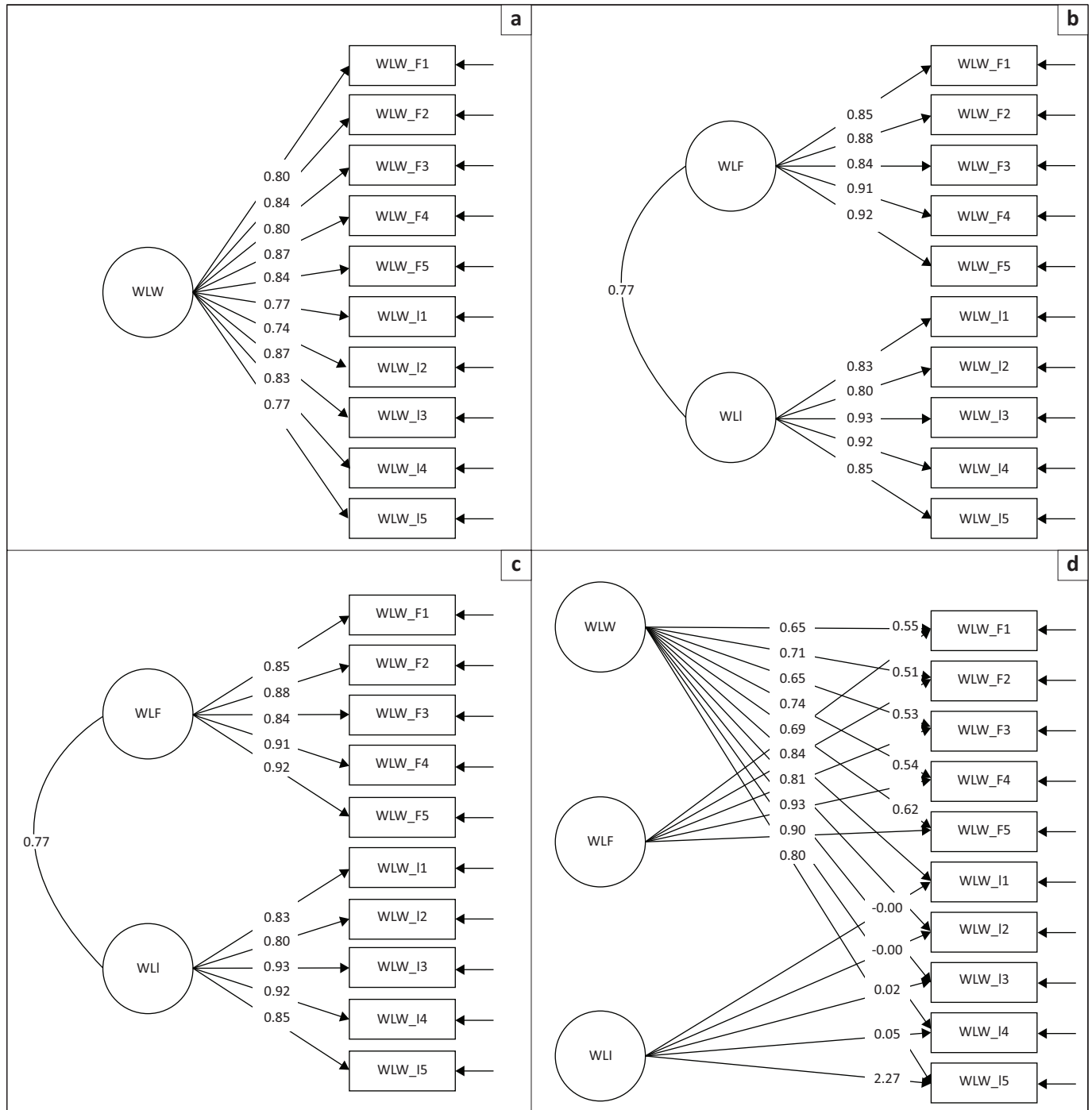
The statistical analysis was conducted using IBM SPSS version 29, with statistical significance set at $p \leq 0.05$. Confirmatory factor analyses (CFA), including bifactor analyses, were conducted using IBM SPSS Amos (version 29), and the Bifactor Indices Calculator (Dueber, 2017) was used to calculate ancillary bifactor indices.

Data screening involved checking for missing values and identifying unengaged responses. In addition, skewness and kurtosis values indicated no substantial deviation from normality. Given the relatively large sample size ($n = 323$), the normality of the sampling distribution could be assumed, drawing on the central limit theorem (Field, 2024). Descriptive statistics were used to analyse the respondents' demographic profiles and examine the main study variables at the item level. Furthermore, Cronbach's alpha was assessed to evaluate the internal consistency of the items (DeVellis & Thorpe, 2022), and the more robust composite reliability (CR) value was also determined, with a threshold of 0.70 required to confirm that the items consistently measured the construct (Cheung et al., 2024).

Bivariate correlations, through Pearson's correlation coefficient (Pearson's r), were examined to assess the strength and direction of the linear relationships between the two sub-dimensions of the WLWS. The strength of the correlations was interpreted using established guidelines (Field, 2024). Specifically, correlations were considered weak if $|r| < 0.3$, moderate if $0.3 \leq |r| < 0.5$ and strong if $|r| \geq 0.5$.

Confirmatory factor analysis (CFA) was conducted to test how well a hypothesised measurement model fits the observed data (construct validity) (Hair et al., 2019). To investigate the factor structure of the WLWS, four competing CFA models were tested (see Figure 1):

- Model 1: A unidimensional CFA model where all items of the WLWS were loaded onto one factor, suggesting that the WLWS measures a single, unidimensional construct.
- Model 2: A first-order CFA model with the scale items loaded onto their respective subscales. This suggests that the WLWS measures two distinct but related constructs.
- Model 3: A second-order factor structure, where the items load onto their respective subscales, and these subscales,



Note: a, Model 1: Unidimensional; b, Model 2: First-order; c, Model 3: Second-order; d, Model 4: Bifactor.

WLW, work-life wellness; WLF, work-life functioning; WLI, work-life interference.

FIGURE 1: Confirmatory factor analysis models and standardised loadings.

in turn, load onto an overarching WLW factor. This model suggests that the WLWS measures a broader construct composed of two specific subconstructs.

- Model 4: A bifactor model (also known as a nested-factor or hierarchical model) includes a general factor (WLW) influencing all variables and group factors influencing specific subsets of those variables.

The unidimensional model was used to determine whether all 10 items of the WLWS are explained by one higher-order WLW construct. This model was compared to a first-order

CFA model, which suggests that the WLWS measures two distinct but related constructs (WLF and WLI) upon which each set of items related to that factor load. This was followed by a second-order model, which suggests that the WLWS measures a broader construct composed of two correlated subconstructs (WLF and WLI).

Researchers Dunn and McCray (2020) and Schaap and Koekemoer (2021) caution against relying solely on goodness-of-fit indices from CFA when assessing the dimensionality of a measurement. They recommend conducting additional

analyses, such as bifactor testing, local indicator misspecification and approximate measurement invariance testing, for a more comprehensive evaluation. The bifactor model offers a more nuanced understanding of a construct's factor structure, particularly when both first- and second-order models demonstrate acceptable fit (Rodrigues et al., 2016a). The bifactor model proposes a general factor (representing overall well-being or life satisfaction) that influences all items, along with orthogonal specific factors that capture the unique variance of each subscale (Reise, 2012). This structure enables the simultaneous examination of shared variance attributable to the general factor and distinct variance associated with the specific factors, providing a comprehensive understanding of the construct's dimensionality (Reise et al., 2010). A key advantage of the bifactor model is its ability to distinguish the influence of the general factor from the specific factors (Reise et al., 2010). The orthogonality of the specific factors is a crucial assumption, meaning they are independent after accounting for the general factor (Federiak, 2020).

Model fit was assessed utilising the Chi-square statistic (χ^2), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Square Error of Approximation (RMSEA) and the Standardised Root Mean Square Residual (SRMR). For CFI and TLI, values above 0.90 and 0.95, respectively, were considered indicative of acceptable model fit (Hair et al., 2019). The RMSEA and SRMR values below 0.08 were considered a good model fit, while RMSEA values below 0.08 were interpreted as reflecting a reasonable fit (Hu & Bentler, 1999). In addition to the aforementioned fit indices, Akaike's Information Criterion (AIC) was employed for model comparison (Sanderson, 2024). Lower AIC values indicate better model fit (MacKenzie et al., 2018).

Several ancillary bifactor indices were calculated using the Bifactor Indices Calculator (Dueber, 2017) to resolve the question of multidimensionality. These include the Explained Common Variance (ECV), which quantifies the proportion of variance in the items attributable to the general factor (Reise et al., 2013). A high ECV (≥ 0.70) suggests that the general factor accounts for a substantial portion of the variance, potentially indicating essential unidimensionality (Rodriguez et al., 2016a). Omega hierarchical (ω_H) further clarifies the proportion of reliable variance in the total score attributable to the general factor (Rodriguez et al., 2016b).

According to Rodriguez et al. (2016b), ω_H should be greater than 0.80 to assume essential unidimensionality. On the other hand, the omega hierarchical subscale (ω_{HS}) measures the proportion of reliable variance in each subscale score that is independent of the general factor, providing insight into the distinctiveness of the subscales (Reise et al., 2010). Factor Determinacy (FD) was also examined, which is the correlation between factor scores and the factors (Pretorius & Padmanabhanunni, 2024). When both ω_H and factor

determinacy exceed 0.80 and are equivalent, essential unidimensionality is supported (Schaap & Koekemoer, 2021). Combined with the standard model fit indices, these indices provide a comprehensive assessment of the bifactor model and its implications for interpreting the WLWS's factor structure.

Finally, measurement invariance was tested to evaluate whether the model was equivalent across different age groups (Leitgöb et al., 2023). This involved a stepwise modelling process where factor configurations, loadings and intercepts are progressively constrained to be equal across groups (Lasker, 2024). The first step entailed testing configural invariance, which determines if the factor structure is consistent across groups (Putnick & Bornstein, 2016). Establishing configural invariance indicates that groups interpret the items of a psychological measure in terms of the same underlying constructs. If configural invariance is supported, the next step is assessing metric invariance, which examines the equivalence of factor loadings across groups (Putnick & Bornstein, 2016). Equal loadings suggest that groups respond to the psychological measure in a similar manner. Subsequent tests of scalar invariance evaluate the equivalence of intercepts, while strict invariance assesses the equivalence of residual variances (Putnick & Bornstein, 2016). Equal intercepts imply that the observed scores on the psychological measure reflect the same level of the target construct across groups, thus enabling meaningful comparisons of means (De Roover, 2021).

Ethical considerations

Ethical clearance was obtained from the Ethics Review Committee of Department of Human Resource Management in the College of Economic and Management Sciences, University of South Africa (ref #2688) and the participating organisation granted permission. Informed consent was obtained from all participants, and assurances of voluntary participation and strict confidentiality were provided.

Results

Descriptive statistics

Table 1 provides a summary of the descriptive statistics (mean and standard deviation) and reliability indicators (Chronbach's alpha and composite reliability) for the variables (WLWS, WLF and WLI) and the bivariate correlations between them. The mean score for the WLWS was 4.50 (standard deviation [SD] = 1.50), suggesting a moderate level of self-rated work-life wellness (7-point Likert scale). For work-life functioning (WLF), the participants scored 4.62 (somewhat agree; SD = 1.58), indicating that they generally perceive a positive balance between work and personal life. In contrast, the mean work-life interference (WLI) score was 3.62 (somewhat disagree; SD = 1.66). This score indicates minimal interference from work in their personal lives (Como & Domene, 2022). It should be noticed that, to compute the overall WLW score, the items of the WLI subscale must be reverse scored.

According to R. Como (personal communication, July 23, 2024), this aligns with the theoretical conceptualisation of WLW, which emphasises a balance between positive (WLF) and negative (WLI) wellness components.

The Cronbach's alpha and composite reliability (CR) coefficients for the overall scale were $\alpha = 0.84$ and $CR = 0.87$, respectively, exceeding the threshold of 0.70 (DeVellis & Thorp, 2022; Hair et al., 2019). Similarly, the subscales demonstrated strong internal consistency and reliability, with WLF showing an $\alpha = 0.94$ and $CR = 0.94$, and WLI also recording an $\alpha = 0.94$ and $CR = 0.94$. These results suggest good construct reliability for the WLWS in the present sample.

The bivariate correlation between the two subscales was $r = 0.72$ ($p < 0.01$; large practical effect), suggesting potential multicollinearity. However, the correlation between the two subscales was not unexpected. It corresponded with Como and Domene's (2022) finding that WLF and WLI represent complementary aspects of work-life functioning and should not be used separately. The high correlations between the two subscales and the overall scale ($r = 0.93$; $p = 0.01$; large practical effect) suggest strong convergent validity, supporting the notion that the two subscales measure the same underlying construct (WLW).

Confirmatory factor analysis models

Confirmatory factor analysis (CFA) was used to evaluate the factorial structure of the WLWS. Four competing measurement models, as depicted in Figure 1, were tested.

Table 2 provides a summary of the results of these analyses.

Model 1 exhibits a poor fit of the observed data. Several key fit indices fall outside acceptable thresholds. Specifically, the CMIN/degrees of freedom [df] ratio of 18.53 far exceeds the recommended value of 3.0, indicating a significant mismatch

between the model and the data. The RMSEA value of 0.23 also exceeds the minimum threshold of 0.05 for good model fit or at least 0.08 for adequate fit. While the SRMR of 0.08 falls within the acceptable range (up to 0.10), it is borderline and not considered ideal (good fit < 0.05). Furthermore, both the CFI and the TLI, at 0.81 and 0.75, respectively, fall well short of the recommended minimums of 0.90 and 0.95. Finally, the AIC for Model 1 (688.68) is considerably higher than those of the alternative models, providing further evidence of its inadequate fit. Taken together, these results strongly suggest that the unidimensional model poorly represents the underlying structure of the data. The data suggests a more complex structure, which was explored in Models 2 and 3.

Models 2 and 3 showed a similar and acceptable model fit. Their fit indices were generally within acceptable ranges: CMIN/ $df = 3.29$ (slightly above the ideal of 3.0), RMSEA = 0.08 (reasonable fit), SRMR = 0.02 (reasonable fit), CFI = 0.98 (above the recommended threshold of 0.90) and TLI = 0.97 (above the recommended threshold of 0.95). The AIC = 153.96 (lower than the value for Model 1). It is important to observe that the identical fit indices observed for Models 2 and 3 do not indicate a violation of the second-order model's assumptions. Instead, they demonstrate that these two models are nested models that are mathematically equivalent (Byrne, 2016). The AIC of 153.96 for Models 2 and 3 was lower than that of Model 1. However, compared to the single-factor model, the improvement in fit offered by these first- and second-order models was minimal.

While the second-factor model (Model 3) provided an acceptable model fit, suggesting that the higher-order WLW factor explains the two subscales (WLF and WLI), the bifactor model (Model 4) challenges this assumption. This model proposes a general WLW factor that affects not only all items but also separate sub-factors that account for variance in the items beyond what is explained by the general factor. A comparison of the first- and second-order models (Models 2 and 3) with the bifactor model (Model 4) suggests that Model 4 offers a statistically significant, although potentially slight, improvement in fit ($\Delta\chi^2 = 42.61$, $p < 0.001$). While the changes in CFI ($\Delta CFI = 0.01$), TLI ($\Delta TLI = 0.007$), RMSEA ($\Delta RMSEA = -0.01$) and SRMR ($\Delta SRMR = 0.006$) are minimal, the AIC difference (AIC = 24.61) is more pronounced. Although the improvement in fit indices is modest, the bifactor model (Model 4), as detailed in Table 2, provides a

TABLE 1: Descriptive statistics and bivariate correlations of the WLWS ($N = 323$).

WLWS	α	CR	$\bar{x}$	SD	1	2	3
Overall WLWS	0.84	0.87	4.50	1.50	-	-	-
WLF	0.94	0.94	4.62	1.58	0.93*	-	-
WLI	0.94	0.94	3.62	1.66	0.93*	0.72*	-

WLWS, work-life wellness scale; WLF, work-life functioning; WLI, work-life interference; α , Cronbach's alpha; CR, composite reliability; $\bar{x}$, mean; SD, standard deviation, r , bivariate correlation.

*, $p \leq 0.01$.

TABLE 2: Confirmatory factor analysis model fit indices ($N = 323$).

Fit Index	Prescribed Threshold	Model 1	Model 2	Model 3	Model 4
Chi-square (CMIN)	-	648.68	111.96	111.96	69.35
df	-	35.00	34.00	34.00	25.00
p -value	-	< 0.001	< 0.001	< 0.001	< 0.001
CMIN/ df	< 3.00	18.53	3.29	3.29	2.77
RMSEA	< 0.05	0.23	0.08	0.08	0.07
SRMR	< 0.05	0.08	0.02	0.02	0.02
CFI	> 0.90	0.81	0.98	0.98	0.99
TLI	> 0.95	0.75	0.97	0.97	0.96
AIC	Low value	688.68	153.96	153.96	129.35

df , degrees of freedom; CMIN/ df , Chi-square per degrees of freedom; RMSEA, Root Mean Square Error of Approximation; SRMR, Standardised Root Mean Square Residual; CFI, Comparative Fit Index; TLI, Tucker-Lewis Index; AIC, Akaike Information Criterion.

richer interpretation of the relationships between the observed variables and the general and specific latent factors. By accounting for both sources of variance (i.e., general and specific factors), Model 4 provides a clearer indication of what each scale measures. It also mitigates potential multicollinearity resulting from the high correlation between WLF and WLI by separating the shared variance (attributed to WLW) from the unique variance (attributed to WLF and WLI). The good model fit for the bifactor model suggests that a structure that includes a general WLW and distinct sub-factors likely best represents the WLW construct.

The relative importance of the general and specific factors was determined by examining the standardised factor loadings from the bifactor model (reported in Table 3).

All items loaded strongly onto the general WLW factor, with loadings ranging from 0.65 to 0.93 – higher than 0.32, which is the rule of thumb value to consider loadings as statistically meaningful (Tabachnick & Fidell, 2019) – confirming that these items contribute substantially to the overall WLW construct. The items designed to measure WLF (WLW_F1 to WLW_F5) also demonstrated moderate to strong loadings on the WLF factor, ranging from 0.51 to 0.62. This suggests that these items capture variance specific to the WLF sub-dimension, distinct from the broader WLW construct. However, the results for the WLI factor were problematic. While WLW_I1 to WLW_I4 exhibited low loadings on the WLI factor, WLW_I5 displayed an exceptionally high loading of 2.27. This, combined with the low loadings of the other WLI items and a near-zero variance estimate for the WLI factor itself, raised serious concerns about the measurement of WLI. This pattern of results is consistent with some of the symptoms observed in Heywood cases, suggesting a potential model misspecification or other issue (Collier, 2020). The high loading for item WLW_I5 was investigated, but no data errors were found. Because of the similarity in wording between WLW_I4 and WLW_I5, a post hoc decision was made to correlate their residuals, hypothesising that this similarity might have introduced shared method variance. This decision was made cautiously and based on the theoretical rationale that the similar wording of these two items might have introduced a method effect. The adjusted bifactor model (Model 5) evaluating local parameter misspecifications on the correlated residuals is presented in Figure 2.

A bifactor model (Model 5) was fitted to the data to examine the structure of WLW, positing a general WLW factor and two specific factors, WLF and WLI. The goodness-of-fit indices and standardised regression weights are reported in Table 4a and Table 4b. To provide a deeper understanding of the WLW's factor structure, ancillary bifactor indices were calculated following the procedures outlined by Rodriguez et al. (2016a). Table 4a and Table 4b presents these indices.

Despite a significant Chi-square statistic ($\chi^2(24) = 58.5$, $p < 0.001$), likely attributable to the sample size, the model

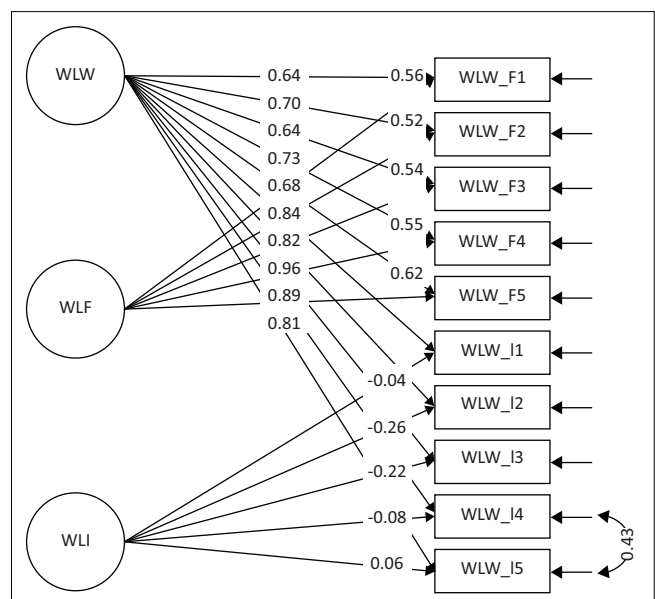
demonstrated acceptable fit across other indices: RMSEA = 0.07, SRMR = 0.02, CFI = 0.99 and TLI = 0.98. The model also exhibited a lower AIC (120.5) compared to alternative models (see Table 2), suggesting a reasonable representation of the data. The general WLW factor emerged as dominant, with all items loading strongly (0.64 to 0.96), confirming their contribution to the overall construct. While items WLW_F1 to WLW_F5 loaded moderately to strongly (0.52 to 0.62) onto the WLF specific factor, the loadings for the WLI items (WLW_I1 to WLW_I5) on their intended specific factor were non-significant. Loadings were consistently low and, critically, several were negative (-0.26 to 0.22). These negative loadings suggest that, after accounting for the general WLW factor, these WLW items are related to the opposite of what WLI is intended to measure. This finding raises serious concerns about the validity of the WLI scale and its distinctiveness from general WLW.

The standardised loadings for both WLF and WLI were substantially reduced when the general WLW factor was included in Model 5, as expected in a bifactor model, indicating that a large portion of the variance previously attributed to these specific factors is now explained by the general WLW factor. This pattern suggests that WLI,

TABLE 3: Standardised bifactor solution for the work-life wellness scale.

Item	WLW	WLF	WLI
WLW_F1	0.65	0.55	-
WLW_F2	0.71	0.51	-
WLW_F3	0.65	0.53	-
WLW_F4	0.74	0.54	-
WLW_F5	0.69	0.62	-
WLW_I1	0.84	-	-0.00
WLW_I2	0.81	-	-0.00
WLW_I3	0.93	-	0.02
WLW_I4	0.90	-	0.05
WLW_I5	0.80	-	2.27

WLW, work-life wellness; WLF, work-life functioning; WLI, work-life interference.



WLW, work-life wellness; WLF, work-life functioning; WLI, work-life interference.

FIGURE 2: Adjusted bifactor model (Model 5).

as currently measured, may not be a psychometrically sound construct, and further investigation is needed. Future research should examine the item wording, reverse coding and the conceptualisation of WLI to determine if the scale can be salvaged or if it should be reconceptualised.

The Explained Common Variance (ECV) for the general WLW factor was 0.78, indicating that this general factor accounts for a substantial portion (78%) of the shared variance among the items. The ECVs for WLF and WLI were much lower (0.41 and 0.03, respectively), indicating that these specific factors explain considerably less of the shared variance in their respective items. The very low ECV for WLI, in particular, strongly suggests that this factor may not be well-defined.

Overall reliability (Omega [ω]), as reflected in Table 5, was high for all factors (WLW = 0.97, WLF = 0.94, WLI = 0.94). However, the hierarchical omega (ω_H), representing variance attributable specifically to the general factor after accounting for the specific factors, was high for WLW (0.85) but substantially lower for WLF (0.38) and near-zero for WLI (0.00). Factor determinacy (FD) was high for WLW (0.98) and WLF (0.92) but suboptimal for WLI (0.73), suggesting that the WLI factor scores are not reliably estimated.

These results suggest that the WLWS primarily measures general work-life wellness, with the general factor accounting

for most of the reliable variance. The strong general factor (high ECV and ω_H) and the weak specific factors (low ECV and ω_H , especially for WLI) support this interpretation. The particularly problematic WLI subscale, with near-zero ECV and ω_H and suboptimal FD, strongly suggests it may not be measuring a valid construct distinct from general WLW and raises serious concerns about its validity. While WLF showed some distinctness, the low ω_H suggests that its contribution to the overall scale score is limited, and most of its variance is also captured by the general WLW factor. Therefore, while WLF showed some distinctness, the WLWS appears to be primarily measuring general work-life wellness.

While the adjustment to the bifactor model improved model fit (Table 4a and Table 4b), this improvement should be interpreted cautiously. Schaap and Koekemoer (2021) observed that such improvements could be because of item-specific method artefacts, such as item redundancy, rather than a true reflection of a shared underlying construct.

Measurement invariance testing

To ensure that the construct being measured is equivalent across different groups, tests for assessing measurement invariance or equivalence (i.e., configural, metric, scalar and strict) of the two-factor structure (Model 3) across age groups were inspected as part of the validation process. The results are summarised in Table 6.

The initial invariance assessment was performed at the configural level to establish whether the same factor structure was present across all age groups (Putnick & Bornstein, 2016). The results indicate good fit to the data ($X^2(68) = 169.67$, $p < 0.001$; CFI = 0.97; TFI = 0.96; RMSEA = 0.07; SRMR = 0.05), supporting the assumption of configural invariance.

Next, metric invariance was examined to determine if the factor loadings were equivalent across age groups (Putnick & Bornstein, 2016). Comparing the metric

TABLE 4a: Fit indices for the adjusted bifactor CFA model ($N = 323$).

Model	Chi-square (CMIN)	df	p-value	CMIN/df	RMSEA	SRMR	CFI	TLI	AIC
Model 5	58.5	24	< 0.001	2.44	0.07	0.02	0.99	0.98	120.5

Note: Goodness-of-fit indices.

df, degrees of freedom; CMIN/df, Chi-square per degrees of freedom; RMSEA, Root Mean Square Error of Approximation; SRMR, Standardised Root Mean Square Residual; CFI, Comparative Fit Index; TLI, Tucker–Lewis Index; AIC, Akaike Information Criterion.

TABLE 4b: Standardised loadings for the adjusted bifactor CFA model ($N = 323$).

Item	WLW	WLF	WLI
WLW_F1	0.64	0.56	-
WLW_F2	0.70	0.52	-
WLW_F3	0.64	0.54	-
WLW_F4	0.73	0.55	-
WLW_F5	0.68	0.62	-
WLW_I1	0.84	-	-0.04
WLW_I2	0.82	-	-0.26
WLW_I3	0.96	-	0.22
WLW_I4	0.89	-	-0.08
WLW_I5	0.81	-	0.06

Note: Standardised regression weights.

WLW, work-life wellness; WLF, work-life functioning; WLI, work-life interference.

TABLE 6: Measurement invariance assessment ($N = 323$).

Model	χ^2	df	p	CFI	TLI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	ΔCFI	ΔTLI	$\Delta RMSEA$	$\Delta SRMR$	Invariance
Configural	169.67	68	< 0.001	0.97	0.96	0.07	0.05	-	-	-	-	-	-	Supported
Metric	187.42	78	< 0.001	0.97	0.96	0.07	0.04	17.74	10	0.002	0.003	0.003	0.000	Supported
Scalar	196.74	88	< 0.001	0.97	0.97	0.06	0.04	9.327	10	0.000	0.004	0.004	0.000	Supported
Strict	244.96	99	< 0.001	0.96	0.96	0.07	0.05	57.546	21	0.011	0.002	0.002	0.009	Partially supported

Note: $p \leq 0.01$.

χ^2 , Chi-square statistic; df, degrees of freedom; CFI, Comparative Fit Index; TLI, Tucker–Lewis Index; RMSEA, Root Mean Square Error of Approximation; SRMR, Standardised Root Mean Square Residual; $\Delta\chi^2$, Change in Chi-square; Δdf , Change in degrees of freedom; ΔCFI , Change in Comparative Fit Index; ΔTLI , Change in Tucker–Lewis Index; $\Delta RMSEA$, Change in Root Mean Square Error of Approximation; $\Delta SRMR$, Change in Standardised Root Mean Square Residual.

invariance model to the configural model revealed acceptable changes in fit indices ($\Delta\chi^2(10) = 17.74, p < 0.001$; $\Delta CFI = 0.002$; $\Delta TLI = 0.003$; $\Delta RMSEA = 0.003$; $\Delta SRMR = 0.002$), supporting the hypothesis of metric invariance. This suggests that the relationship between the items and their respective latent factors was consistent across age groups, allowing for meaningful comparisons of factor correlations.

Scalar invariance was then tested to assess the equivalence of item intercepts across age groups (Putnick & Bornstein, 2016). The scalar invariance model, when compared to the metric invariance model, also demonstrated acceptable changes in fit indices ($\Delta\chi^2(10) = 9.327, p < 0.001$; $\Delta CFI = 0.000$; $\Delta TLI = 0.004$; $\Delta RMSEA = 0.004$; $\Delta SRMR = 0.000$). This indicates that individuals with the same level of latent factor tended to respond similarly to the items, regardless of their age. Therefore, comparisons of latent means across age groups are considered valid and practical.

Finally, strict invariance was examined, assessing the equality of residual variances across age groups. While metric and scalar invariance had been supported, the test of strict invariance returned mixed results. The Chi-square difference test was significant ($\Delta\chi^2(21) = 57.546, p < 0.001$), suggesting that the strict invariance model fit significantly worse than the scalar invariance model. Although the changes in TLI ($\Delta TLI = 0.002$) and RMSEA ($\Delta RMSEA = 0.002$) were within acceptable thresholds, the change in CFI ($\Delta CFI = 0.011$) was slightly above the recommended cutoff of 0.01. These findings indicate that strict invariance was not fully supported, suggesting that the residual variances of at least some items differ across age groups.

In summary, the results suggest that the WLWS measures the same underlying construct across groups (configural), with the same relationships between items and factors (metric), and with equal intercepts (scalar). However, the precision of the measurement (residual variance) is not entirely consistent across groups. Although strict invariance (equal residual variances) was not fully supported, the establishment of scalar invariance is sufficient to justify the practical use of group comparisons.

Discussion

Validating wellness questionnaires in the South African context is crucial for ensuring accurate and culturally relevant assessments of employee well-being (Rautenbach & Rothmann, 2017). While previous research has explored various well-being measures in South Africa, the Work-Life Wellness Scale (WLWS) (Como & Domene, 2022) is yet to be rigorously evaluated in this context. This study addresses this gap by examining the psychometric properties of the WLWS in a South African sample, focusing on its internal structure, reliability, dimensionality and measurement invariance across age groups. The findings provide strong support for the internal consistency and essential unidimensionality of the WLWS and largely support

measurement invariance across age groups, although full strict invariance was not completely achieved. While further research is required to fully establish the scale's construct validity, particularly regarding convergent and discriminant validity, this study offers preliminary evidence for the WLWS as a potentially valuable tool for assessing work-life wellness in South African settings. This can inform HR policies, guide intervention development and contribute to a deeper understanding of employee well-being in the country.

Summary of findings

The descriptive statistics reveal that the mean score for the WLWS was 4.50, reflecting a moderate level of perceived work-life wellness. This suggests that, on average, participants feel they have a moderate ability to balance the demands of both work and personal life. Although the WLWS includes items related to work-life functioning (WLF) and work-life interference (WLI), the findings of this study align with expectations from a bifactor model, where a general factor explains most of the variance in the specific factors. This challenges the independence of WLF and WLI as separate constructs.

Given this, the results indicate that the WLI factor, as currently measured, may not be a psychometrically reliable construct within this South African sample. Specifically, the scores on both the WLF and WLI item sets appear to reflect overall work-life wellness rather than distinct aspects of functioning and interference. As a result, interpreting the mean scores for these item sets separately may be misleading, as they are primarily driven by the general work-life wellness factor. Considering the relatively recent development of the work-life wellness construct and the limited availability of comparable data, these findings should be understood within the context of the present sample.

This research aimed to validate the WLWS in a South African context, evaluate its dimensionality and test for invariance across age groups. Regarding the first sub-objective, namely, to validate the WLWS, the study provides evidence for the reliability and, to a large extent, the construct validity of the overall WLWS score in a South African sample. The strong internal consistency of the scale, as evidenced by high Cronbach's alpha (0.84) and composite reliability (0.87) coefficients, suggests that the items consistently measure the overall work-life wellness construct. While the WLWS includes items related to work-life functioning (WLF) and work-life interference (WLI), the scale behaved essentially as a unidimensional measure of overall WLW in this study. Therefore, these high-reliability coefficients primarily reflect the strong general work-life wellness factor, not the unique variance of distinct WLF and WLI subscales.

Dimensionality analysis further supported the essential unidimensionality of the WLWS. A bifactor model analysis

demonstrated an improved fit compared to alternative models, suggesting a dominant general WLW factor. Ancillary bifactor indices (ECV and OmegaH) confirmed this, showing the general factor accounts for a substantial portion of the variance (78%) and reliable variance (97%) in the items. This contradicts Como and Domene's (2022) proposed two-factor structure (WLF and WLI). While WLF and WLI item sets can be examined, they should not be treated as independent subscales.

The WLI subscale proved particularly problematic, with near-zero ECV and OmegaH, as well as suboptimal FD, raising concerns about its validity. Specifically, item WLW_I5 exhibited an exceptionally high and likely spurious loading on the WLI factor, while other WLI items had very low loadings. This suggests a potential measurement artefact or item-specific issue with WLW_I5, casting doubt on the validity of the entire WLI item set. While WLW_I4 also showed a relatively high loading on WLI, suggesting some shared variance, post hoc analyses indicated that combining WLW_I4 and WLW_I5 improved model fit. However, this improvement should be interpreted cautiously. These items shared similar wording and sentence structure, suggesting item-specific method artefacts, likely because of item redundancy rather than a true reflection of a shared underlying construct. This redundancy could explain the improved model fit – essentially reducing the influence of the method artefact – but does not address the fundamental issue with the WLI item set. While WLF shows some evidence of distinctness, the overall pattern strongly suggests that the WLWS is best represented as measuring a dominant general factor of work-life wellness. This highlights the importance of looking beyond overall model fit statistics, especially in bifactor models and examining factor loadings and other diagnostic information to avoid over-interpreting global fit indices (Bornoalova et al., 2020). Further research is needed to determine if WLF and WLI can be validly treated as separate subscales or if a reconceptualisation of the scale's structure is necessary.

Concerning the third objective, testing for invariance across age groups, the study provides substantial support for configural, metric and scalar invariance. However, strict invariance was not fully supported, suggesting that the residual variances of at least some WLWS items are not equivalent across age groups. Consequently, although comparisons of latent means (i.e., comparing the underlying construct scores) across age groups are valid, comparisons of observed WLWS scores (i.e., raw item scores) should be interpreted with caution, as differences in observed scores may reflect variations in residual variance rather than true differences in the underlying construct. When conducting invariance testing, researchers should primarily focus on comparing 'latent means' rather than observed scores and always report effect sizes because this ensures that any observed differences between groups truly reflect the underlying construct being measured, not just variations in

how the construct is measured across different groups (Putnick & Bornstein, 2016). Future research should investigate the source of this non-invariance and explore ways to address it.

Theoretical and practical implications of the study

This study makes several key contributions. Theoretically, this research contributes to our understanding of work-life wellness by demonstrating that, despite its potential multidimensionality (Como & Domene, 2022), the Work-Life Wellness Scale (WLWS) functions primarily as a unidimensional measure, capturing a dominant general factor. The study also sheds light on the complexities of the work-life interference (WLI) construct, raising important theoretical questions about its measurement. Empirically, the use of bifactor modelling and ancillary indices provides a practical example for evaluating scale dimensionality. Finally, the findings regarding measurement invariance across age groups contribute to our understanding of measurement equivalence.

Practically, the WLWS provides South African organisations with a psychometrically sound tool to assess employees' levels of work-life wellness. Organisations can use the overall WLW score to gain insights into employees' perceived level of work-life wellness. Based on these insights, organisations can develop targeted interventions to promote work-life wellness and evaluate their effectiveness. These interventions could include organisational-level initiatives, such as flexible work arrangements, remote work options and mental health support (e.g., stress management training) (Gupta et al., 2024), aimed at addressing common work-life challenges. Personal interventions, such as behaviour-based strategies (e.g., managing role conflict and creating role balance) and cognition-based strategies (e.g., segmenting roles), must also be encouraged (Sirgy & Lee, 2023).

Moreover, the data collected through the WLWS can enhance existing wellness programmes and employee assistance programmes (EAPs) by informing tailored work-life wellness workshops that address specific employee needs and demographics, enabling organisations to provide focused support and guidance.

Furthermore, inviting experts in work-life wellness to lead these workshops can offer valuable insights and strategies, ensuring that the initiatives aimed at improving well-being are culturally relevant and suited to the diverse South African workforce.

Limitations and recommendations for future research

Despite efforts to ensure scientific rigour, several limitations should be acknowledged. Data were collected from a single retail organisation, limiting the findings' generalisability to other industries. Using purposive sampling, focusing on employees who participated in a wellness programme,

may have introduced selection bias (Benoot et al., 2016). Participants in the wellness programme could be more engaged with wellness issues than the broader workforce. Although this approach required an element of self-selection, which could limit the diversity of perspectives, it encouraged participation from individuals with a vested interest in the research, resulting in greater motivation to engage and share their views (Zickar & Keith, 2023). Consequently, the findings are not generalisable to other workplace contexts, and further validation of the Work-Life Wellness Scale (WLWS) in diverse settings is recommended. Finally, while the study examines the internal structure and some aspects of reliability, it lacks data on convergent and discriminant validity. This limits the scope of construct validity evidence, as it does not demonstrate relationships with other wellness measures or related constructs.

Conclusion

This study contributes to the literature by providing valuable insights into the psychometric properties of the WLWS within a South African context. The findings refine our understanding of work-life wellness, revealing that the WLWS, while potentially reflecting a multidimensional construct (Como & Domene, 2022), primarily captures a dominant general factor, suggesting essential unidimensionality. This finding has important implications for both the theoretical understanding and the practical application of the WLWS.

Practically, this study offers clear recommendations for the appropriate use of the WLWS, emphasising the interpretation of the overall WLW score. These findings can inform the development of more effective interventions and policies aimed at promoting work-life wellness in South African organisations. Future research should prioritise addressing the identified limitations to enhance the scale's utility and contribute to a deeper understanding of work-life wellness in diverse populations. By utilising insights from the WLWS, organisations can improve their wellness and employee assistance programmes, ensuring they address the unique needs of the South African workforce. This study highlights the importance of measuring and addressing work-life wellness to promote healthier and more balanced work environments.

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Authors' contributions

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References

- Benoot, C., Hannes, K., & Bilsen, J. (2016). The use of purposeful sampling in a qualitative evidence synthesis: A worked example on sexual adjustment to a cancer trajectory. *BMC Medical Research Methodology*, 16(1), 1–12. <https://doi.org/10.1186/s12874-016-0114-6>
- Bhatasana, D. (n.d.). *Employee wellbeing: A key to retention and productivity*. Retrieved from <https://www.hrfuture.net/workplace-culture/culture-workplace-happiness/employee-wellbeing-a-key-to-retention-and-productivity/>
- Botha, D., & Coetzee, R. (2022). COVID-19 Pandemic: Perspectives on employee engagement, work from home and an employee wellness programme in a debt collection organisation in Gauteng, South Africa. *African Journal of Employee Relations*, 46, 1–28. <https://doi.org/10.25159/2664-3731/9235>
- Byrne, B. M. (2016). *Structural Equation Modeling with Amos: Basic concepts, applications and programming* (3rd ed.). Routledge.
- Carvalho, D., Aguiar, P., & Ferrinho, P. (2020). Questionnaire validation: A user guide. *Authorea*, 1–7. <https://doi.org/10.22541/au.159110341.17490452>
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745–783. <https://doi.org/10.1007/s10490-023-09871-y>
- Choi, M.S., Marçal, K.E., & Showalter, K. (2024). Disparities in the quality of working life among older workers: Housing conditions and life satisfaction with latent class analysis. *Journal of Applied Gerontology*, 43(11), 1630–1639. <https://doi.org/10.1177/07334648241246484>
- Collier, J. E. (2020). *Applied Structural Equation Modeling using AMOS*. Routledge.
- Como, R. E., & Domene, J. F. (2022). Work-Life Wellness Scale: Initial test development in a sample of remote workers. *Asia Pacific Career Development Journal*, 5(1), 3–12. http://AsiaPacificCDA.org/Resources/APCDJ/A0005_1_01.pdf
- Como, R., Hambley, L., & Domene, J. (2021). An exploration of work-life wellness and remote work during and beyond COVID-19. *Canadian Journal of Career Development*, 20(1), 46–56. <https://cjd-crdc.ceric.ca/index.php/cjd/article/view/92/109>
- Creswell, J. W., & Creswell, J. D. (2022). *Research Design* (6th ed.). SAGE.
- Cromhout, A., Schutte, L., Wissing, M. P., & Schutte, W. D. (2022). Further investigation of the dimensionality of the Questionnaire for Eudaimonic Well-Being. *Frontiers in Psychology*, 13, 1–15. <https://doi.org/10.3389/fpsyg.2022.795770>
- De Rooover, K. (2021). Finding clusters of groups with measurement invariance: Unraveling intercept non-invariance with mixture multigroup factor analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, 28(5), 663–683. <https://doi.org/10.1080/10705511.2020.1866577>
- DeVellis, R. F., & Thorpe, C. T. (2022). *Scale development: Theory and applications* (5th ed.). SAGE.
- Diessel, J. (2007). *Validation of a scale to measure time perspective in an African context* [Mini-Dissertation]. North-West University.

- Du Plessis, G. A., & Guse, T. (2017). Validation of the scale of positive and negative experience in a South African student sample. *South African Journal of Psychology*, 47(2), 184–197. <https://doi.org/10.1177/0081246316654328>
- Du Plessis, M. (2022). Working remotely in the new normal: Towards a conceptual framework for managing employee well-being. In I. L. Potgieter & N. Ferreira (Eds.), *Managing human resources: The new normal* (pp. 165–191). Springer Nature. https://doi.org/10.1007/978-3-031-09803-1_10
- Dueber, D.M. (2017). *Bifactor Indices Calculator: A Microsoft Excel-based tool to calculate various indices relevant to bifactor CFA models*. Retrieved from https://uknowledge.uky.edu/edp_tools/1/
- Dunn, K.J., & McCray, G. (2020). The place of the bifactor model in confirmatory factor analysis investigations into construct dimensionality in language testing. *Frontiers in Psychology*, 11:1357. <https://doi.org/10.3389/fpsyg.2020.01357>
- Fatima, F., Oba, P., & Sony, M. (2022). Exploring employee well-being during the COVID-19 remote work: Evidence from South Africa. *European Journal of Training and Development*, 47(10), 9–11. <https://doi.org/10.1108/EJTD-06-2022-0061>
- Federiak, D. (2020). Calibrating the test of relational reasoning: New information from oblique bifactor models. *Frontiers in Psychology*, 11, 1–10. <https://doi.org/10.3389/fpsyg.2020.02129>
- Field, A. (2024). *Discovering Statistics Using IBM SPSS Statistics* (6th ed.). SAGE.
- Fisher, G. G., Bulger, C. A., & Smith, C. S. (2009). Beyond work and family: A measure of work/nonwork interference and enhancement. *Journal of Occupational Health Psychology*, 14(4), 441–456. <https://doi.org/10.1037/a0016737>
- Gupta, J., Krsihnapa, R., Sharma, A., & Khalid, M. (2024). Employee well-being initiatives: A critical analysis of HRM practices. *Educational Administration: Theory and Practice*, 30(5), 6808–6815. <https://doi.org/10.53555/kuey.v30i5.4020>
- Haar, J.M., Sune, A., Russo, M., & Ollier-Malaterre, A. (2019). A cross-national study on the antecedents of work-life balance from the fit and balance perspective. *Social Indicators Research*, 142(1), 261–282. <https://doi.org/10.1007/s11205-018-1875-6>
- Hair, J.F., Black, W.C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate Data Analysis* (8th edn.). Cengage Learning.
- Hu, L.T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Laher, S., & Cockcroft, K. (2013). *Psychological assessment in South Africa: Research and applications*. Wits University Press.
- Lasker, J. (2024). Measurement invariance testing works. *Applied Psychological Measurement*, 48(6), 257–275. <https://doi.org/10.1177/01466216241261708>
- Leavy, P. (2022). *Research Design* (2nd ed.). Guilford.
- Leitgöb, H., Seddig, D., Asparouhov, T., Behr, D., Davidov, E., De Roover, K., Jak, S., Meitinger, K., Menold, N., Muthén, B., Rudnev, M., Schmidt, P., & Van de Schoot, R. (2023). Measurement invariance in the social sciences: Historical development, methodological challenges, state of the art, and future perspectives. *Social Science Research*, 110, 1–30. <https://doi.org/10.1016/j.ssresearch.2022.102805>
- Lucini, D., Pagani, E., Capria, F., Galiano, M., Marchese, M., Cribellati, S., & Parati, G. (2023). Age influences on lifestyles and stress perception in the working population. *Nutrients*, 15, 1–11. <https://doi.org/10.3390/nu15020399>
- MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L.L., & Hines, J.E. (2018). Fundamental Principles of Statistical Inference. In D.I. MacKenzie, J.D. Nichols, J.A. Royle, K.H. Pollock, L.L. Bailey, & J.E. Hines (Eds.), *Occupancy Estimation and Modeling* (pp. 71–111). Elsevier. <https://doi.org/10.1016/B978-0-12-407197-1.00004-1>
- Mahdia, A. (2024). The role of human resource management in employee well-being and mental health: A systematic literature review. *Management Studies and Business Journal*, 1(3), 286–303. <https://doi.org/10.62207/phea4z38>
- Mhlongo, P.S., du Plessis, C., & Weidemann, A. (2022). Motivation for English language learning: First steps in creating a more inclusive questionnaire. *Per Linguam*, 38(1), 118–141. <https://doi.org/10.5785/38-1-987>
- Mpondo, F., Wray, C., Norris, S.A., Stein, A.D., Stein, A., & Richter, L.M. (2021). Assessing psychological well-being measures among South African adults in the birth to twenty plus cohort. *African Journal of Psychological Assessment*, 3, 1–7. <https://doi.org/10.4102/ajopa.v3i0.44>
- Nel, P., Van Zyl, E.S., Akwa-Nde, A., & Mokuoane, M.L. (2019). Structure of the Experience of Work and Life Circumstances Questionnaire among South African employees in the financial services and health sectors. *Journal of Psychology in Africa*, 29(3), 203–207. <https://doi.org/10.1080/14330237.2019.1616422>
- Pretorius, T.B., & Padmanabhanunni, A. (2024). Dimensionality in confirmatory factor analysis is not in the eye of the beholder: Ancillary bifactor statistical indices illuminate dimensionality and reliability. *International Journal of Psychology*, 60(1), e13266. <https://doi.org/10.1002/ijop.13266>
- Putnick, D.L., & Bornstein, M.H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review*, 41, 71–90. <https://doi.org/10.1016/j.dr.2016.06.004>
- Rautenbach, C., & Rothmann, S. (2017). Psychometric validation of the Flourishing-at-Work Scale – Short Form (FWS-SF): Results and implications of a South African study. *Journal of Psychology in Africa*, 27(4), 303–309. <https://doi.org/10.1080/14330237.2017.1347748>
- Reise, S.P., Scheines R., Widaman K.F., & Haviland M.G. (2013). Multidimensionality and structural coefficient bias in structural equation modeling: A bifactor perspective. *Educational and Psychological Measurement*, 73(1), 5–26. <https://psycnet.apa.org/doi/10.1177/0013164412449831>
- Reise, S.P., Moore, T.M., & Haviland, M.G. (2010). Bifactor models and rotations: Exploring the extent to which multidimensional data yield univocal scale scores. *Journal of Personality Assessment*, 92(6), 544–559. <https://doi.org/10.1080/00223891.2010.496477>
- Rodriguez, A., Reise, S.P., & Haviland, M.G. (2016a). Applying bifactor statistical indices in the evaluation of psychological measures. *Journal of Personality Assessment*, 98(3), 223–237. <https://doi.org/10.1080/00223891.2015.1089249>
- Rodriguez, A., Reise, S.P., & Haviland, M.G. (2016b). Evaluating bifactor models: Calculating and interpreting statistical indices. *Psychological Methods*, 21(2), 137–150. <https://doi.org/10.1037/met0000045>
- Sanderson, S. (2024). *Understanding the Akaike Information Criterion (AIC)* [Blog post]. SteveOnData. Retrieved from <https://www.spsanderson.com/steveondata/posts/2024-05-06/>
- Saunders, M.N.K., Lewis, P., & Thornhill, A. (2023). *Research Methods for Business Students* (9th ed.). Pearson.
- Schaap, P., & Koekemoer, E. (2021). Determining the dimensionality and gender invariance of the MACE work-to-family enrichment scale using bifactor and approximate invariance tests. *South African Journal of Industrial Psychology*, 47(0), a1821. <https://doi.org/10.4102/sajip.v47i0.1821>
- Sirgy, M.J., & Lee, D.-J. (2023). *Work-life balance*. Cambridge University Press. <https://doi.org/10.1017/9781009281782>
- Stockton, M.A., Mazinyo, E.W., Mlanjeni, L., Sweetland, A.C., Scharf, J.Y., Nogemane, K., Ngcelwane, N., Basaraba, C., Bezuidenhout, C., Sansbury, G., Olivier, D., Grobler, C., Wall, M.M., Medina-Marino, A., Nobatyi, P., & Wainberg, M.L. (2024). Validation of screening instruments for common mental disorders and suicide risk in South African primary care settings. *Journal of Affective Disorders*, 362, 161–168. <https://doi.org/10.1016/j.jad.2024.06.071>
- Tabachnick, B.G., & Fidell, L.S. (2019). *Using multivariate statistics* (7th ed.). Pearson Education.
- Temane, L., Khumalo, I. P., & Wissing, M. P. (2014). Validation of the Meaning in Life Questionnaire in a South African context. *Journal of Psychology in Africa*, 24(1), 51–60. <https://doi.org/10.1080/14330237.2014.904088>
- Terry, P. E. (2024). Research findings journalists cannot resist: A tale of three mental health and well-being studies. *American Journal of Health Promotion*, 38(4), 459–463. <https://doi.org/10.1177/08901171241232248>
- Trivella, C. (2023). *Why employers need to care about every aspect of employees' health*. Retrieved from <https://www.forbes.com/councils/forbeshumanresources/council/2023/07/11/why-employers-need-to-care-about-every-aspect-of-employees-health/>
- Zanon, C., Brenner, R.E., Nunes Baptista, M., Vogel, D.L., Rubin, M., Al-Darmaki, F.R., Gonçalves, M., Heath, P.J., Liao, H.Y., Mackenzie, C.S., Topkaya, N., Wade, N.G. & Zlati, A. (2021). Examining the dimensionality, reliability, and invariance of the Depression, Anxiety, and Stress Scale–21 (DASS-21) across eight countries: *Assessment*, 28(6), 1531–1544. <https://doi.org/10.1177/1073191119887449>
- Zhang, Y., & Aryadoust, V. (2022). A systematic review of the validity of questionnaires in second language research. *Education Sciences*, 12(10), 1–32. <https://doi.org/10.3390/educsci12100723>
- Zickar, M.J., & Keith, M.G. (2023). Innovations in sampling: Improving the appropriateness and quality of samples in organizational research. *Annual Review of Organizational Psychology and Organizational Behavior*, 10(1), 315–337. <https://doi.org/10.1146/annurev-orgpsych-120920-052946>