1 **Measuring burnout in social work: factorial validity of the Maslach Burnout**

2 **Inventory-Human Services Survey**

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1   **Abstract**

2   Several studies challenge the three-dimensional structure of the Maslach Burnout Inventory-

3   Human Services Survey (MBI-HSS), citing alternative measurement models including

4   bifactor models. Whilst bifactor models have merit, if data sampling violates assumptions of

5   Stochastic Measurement Theory (SMT) the bifactor model requires modification prior to

6   application. The present study compared five alternative MBI-HSS factor models using both

7   Confirmatory Factor Analysis (CFA) and Exploratory Structural Equation Modeling (ESEM).

8   Data from a cross-sectional survey of United Kingdom (UK) social workers was examined (N

9   = 1257), with validation analyses conducted in an independent sample (N = 162). Bifactor

10   models, re-specified to account for SMT, provided good fit. However, improved fit was

11   observed for a bifactor-ESEM specification, in both test ($\chi2$ = 1112.93, df = 149, p < .001,

12   CFI = .969, RMSEA = .072 [90% CI .068, .076]) and validation ($\chi2$ = 227.89, df = 149, p <

13   .001, CFI = .978, RMSEA = .057 [90% CI .042, .072]) samples. The results confirm the

14   MBI-HSS possesses a bifactor structure in UK social workers when SMT is considered, and

15   that bifactor-ESEM may provide a better framework to examine MBI-HSS.

16   **Keywords-burnout; MBI-HSS; social work; bifactor; bifactor-ESEM**

1   **Introduction**

2   The Maslach Burnout Inventory-Human Services Survey (MBI-HSS; Maslach, Jackson &

3   Leiter, 1996) is the most cited burnout measure (Worley, Vassar, Wheeler & Barnes, 2008).

4   It comprises three subscales posited to measure the latent dimensions of burnout: emotional

5   exhaustion (EE), depersonalisation (DP) and reduced personal accomplishment (PA). The

6   respondent receives three separate scores, each reflecting a unique aspect of the phenomenon.

7   These dimensions have shown differential relationships with turnover intentions, job

8   satisfaction and organisational commitment (Lee & Ashforth, 1996).

9   Whilst it has been accepted that these latent dimensions possess some

10   interrelationship, there has been no consensus on the number of dimensions. Two, four and

11   five-factor solutions have been reported across a wide range of occupations (Chao,

12   McCallion & Nickle 2011; Densten, 2001; Walkey & Green, 1992). Furthermore, the

13   literature suggests 16 (Stalker, Harvey, Frensch, Mandell & Adams, 2008), 18 (Yadama &

14   Drake, 1995) and 19 (Kim & Ji, 2009) item scales to be more parsimonious. There is also

15   evidence of additional scale complexity, with some items loading onto more than one factor.

16   Items 12 and 16 are particularly problematic and are frequently omitted in response (Kim &

17   Ji, 2009; Maslach et al., 1996).

18   Recently, it has been argued the debate surrounding the MBI-HSS factor structure

19   may be settled if one uses a bifactor approach (Mészáros, Ádám, Szabó, Szigeti & Urbán,

20   2014). Bifactor models allow the simultaneous estimation of a general factor and specific

21   factors, similar to a higher-order model. Unlike higher-order models, the bifactor approach

22   allows all indicators to load onto a general factor and their specific factor. In the higher-order

23   model, the influence of the general factor on the indicators is mediated via the first order

24   factors. Following superior fit with a bifactor model, Mészáros and colleagues (2014)

1   concluded only the PA items explained additional variance in burnout, over and above a

2   general burnout factor. However, the correlated first-order factor model is nested within the

3   bifactor model (Yung, Thissen & McLeod, 1999) and the bifactor model will always provide

4   better fit than a correlated factors model (Reise, 2012).

5   Despite providing superior fit, Mészáros and colleagues (2014) offer little explanation

6   of unusual factor loading patterns identified within their bifactor solution. Item 4, a PA item,

7   did not load significantly onto their *'global burnout'* general factor. Item 13 exhibited a

8   negative loading on the EE specific factor, which was at odds with the valence of other

9   indicators of this specific factor. Despite this, Mészáros and colleagues (2014) do not

10   speculate as to why they have occurred, how they relate to the literature, or what implications

11   they have for score computation.

12   Anomalous results using bifactor approaches occur so frequently that Eid, Geiser,

13   Koch and Heene (2017) question the appropriateness of their application. Eid and colleagues

14   note that in many cases indicators are found to have small loadings, non-significant loadings,

15   or even negative loadings on their specific factor, as observed in Mészáros et al., (2014).

16   Such findings are unexpected given loading patterns are often regular when modelled as a

17   simpler correlated first-order factor model (Eid et al., 2017). They further argue that not all

18   indicators load onto the general (g) factor, another unexpected anomalous result.

19   Eid and colleagues (2017) argue traditional bifactor models in many empirical studies

20   violate assumptions underlying Stochastic Measurement Theory (SMT). When a series of

21   observed indicators are used in a random population sample, only one level of sampling has

22   occurred. However, unless the domain specific factors are also selected at random (second

23   level of sampling), g cannot be considered a true random variable. Where two-level sampling

24   is impossible, Eid et al., (2017) offer alternative strategies to ensure the general and specific

1 factors remain true random variables. One approach is to use one specific factor as a

2 comparison standard (*S-1* model, Figure 1a), whilst the second approach uses one item as a

3 reference indicator (*S·I-1*, Figure 1b) (Eid et al., 2017).
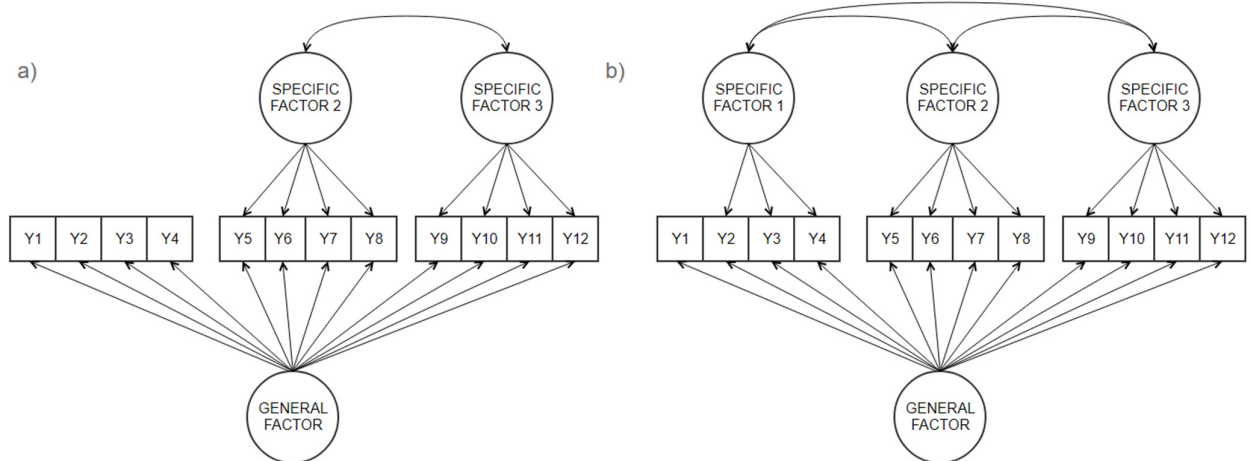
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5 *Figure 1: Alternative bifactor model parameterisations where single-level sampling has*

6 *occurred (Eid et al., 2017), where a) S-1 model and b) S·I-1 model.*

7   The superior performance of bifactor specifications of the MBI-HSS may result from

8 an inherent bias to accommodate unidentified model complexity. Higher-order factor models

9 have fewer parameters than bifactor models, and thus will never fit better from a chi-square

10 perspective (Gignac, 2016). As such, items that cross-load are more easily accommodated by

11 the bifactor approach.

12   When specified as a correlated factor model, MBI-HSS items 6, 12 and 16 have been

13 found to cross-load onto other latent dimensions (Kanste, Miettunen & Kyngäs, 2006; Kim &

14 Ji, 2009). The Independent Cluster Model (ICM) constraints of CFA assumes that cross-

15 loadings between items and non-target factors are exactly zero (Howard, Gagné, Morin &

16 Forest, 2016). However, many questionnaire items are rarely unique indicators of a single

17 construct and may tap into additional latent factors that have some conceptual relationship

1   (Morin, Arens & Marsh, 2016). Thus, it is prudent to examine MBI-HSS using Exploratory

2   Structural Equation Modeling (ESEM) to examine these cross-loaded items in greater detail.

3   Previous research involving social workers has suggested a better fitting latent

4   structure can be achieved using reduced items scales (Kim & Ji, 2009; Stalker et al., 2008;

5   Yadama & Drake, 1995). These authors deleted items due to high inter-item correlations,

6   cross-loadings and small squared multiple correlations, concluding that improved fit indices

7   indicated better fitting models. However, comparing models with different numbers of items

8   is problematic. Furthermore, the failure to cross-validate findings and examine the

9   relationships with external criteria limits the utility of these alternative specifications.

10   The present study sought to compare a correlated first-order factor model of the MBI-

11   HSS with alternative bifactor specifications compatible with SMT, in a social work sample.

12   Furthermore, we sought to examine whether re-specification within an ESEM framework

13   would provide a better fitting latent structure. Additionally, the performance of the optimal

14   measurement model in a validation sample, and its relationship with an external criterion,

15   resilience, was examined. A clearer understanding of the true measurement model of burnout

16   among social workers is imperative for a more accurate assessment of burnout. Since most

17   previous research has examined child protection social workers, the present study further

18   sought to examine the factorial validity of the MBI-HSS in a more heterogeneous sample of

19   social work specialisms.

20   **Method**

21   *Sample*

22   Data from cross-sectional surveys of social workers in the United Kingdom (UK) was

23   examined. In the test sample the survey was emailed to all social workers registered with

24   Community Care©. A total of 1,257 participants completed the MBI-HSS component of the

1   survey. Validation analyses were conducted in independently collected data $(N = 162)$

2   reported in McFadden, Mallett, Campbell and Taylor (2019). There were no issues of missing

3   data on MBI-HSS items in either sample. Sample characteristics can be observed in Table 1.

4

5   *Table 1*

6   *Frequencies for demographic characteristics of test (N=1257) and validation (N=162)*
7   *samples*

Characteristic		Test sample	Validation sample
		n (%)	*n (%)*
Gender	Female	1028 (81.8)	140 (86.4)
	Male	201 (16)	22 (13.6)
Age (years)	18-25	48 (3.8)	14 (8.6)
	26-35	284 (22.6)	76 (46.9)
	36-45	286 (22.8)	43 (26.5)
	46-55	395 (31.4)	23 (14.2)
	56+	229 (18.2)	6 (3.7)
Residence	England	1087 (86.5)	-
	Scotland	61 (4.9)	-
	Wales	67 (5.3)	-
	Northern Ireland	15 (1.2)	162 (100)
Practice area	Child protection	358 (28.5)	162 (100)
	Other children's services	234 (18.6)	-
	Older peoples' services	238 (18.9)	-
	Mental health	131 (10.4)	-
	Adult disability services	121 (9.6)	-

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1   *Measures*

2   Burnout was assessed using the 22-item MBI-HSS (Maslach et al., 1996), which asks

3   respondents how frequently they experience feelings in line with item statements. Items were

4   scored on a seven-point scale from 0 (*never*) to 6 (*every day*). The EE subscale (9 items)

5   measured feelings of being emotionally overextended by one's work. The DP subscale (5

6   items) measured an impersonal response toward recipients of one's care. The PA subscale (8

7   items) measured feelings of competence in one's work. Higher scores on the EE and DP

8   subscales, accompanied with lower PA scores, indicated a higher degree of burnout. The

9   MBI-HSS has shown good reliability in previous social work studies (Kim & Ji, 2009;

10   Yadama & Drake, 1995).

11   In the validation sample resilience was measured using the self-report Resilience

12   Scale (RS14: Wagnild & Young, 2009). Items were scored on a seven-point scale from 1

13   (*strongly disagree*) to 7 (*strongly agree*) and summated to form an overall score whereby

14   higher scores indicate greater resilience. The RS-14 has shown high internal consistency

15   (Aiena, Baczwaski, Schulenberg & Buchanan, 2014; Taku, 2014), as well as significant

16   correlations in expected directions with life satisfaction and psychological distress, in both

17   clinical and non-clinical samples (Aiena et al., 2014). Higher RS14 scores were predictive of

18   lower EE and higher PA among physicians (Taku, 2014).

19   *Analyses*

20   Five confirmatory factor models were specified (Figure 2) and estimated in the test

21   sample using Mplus 8.1 (Muthén & Muthén, 2018). Model A comprised the correlated three-

22   factor solution hypothesised by Maslach et al., (1996). Three *S-1* models were specified,

23   aimed at representing item heterogeneity differently, with EE, DP and PA as the reference

24   domains, respectively. In Model B, *g* represents the individuals EE corrected for

25   measurement error. In this model, the DP and PA factors represent whether a participant has

1   higher or lower DP and PA than one would expect given their EE level. In Model C, *g*

2   signifies DP with the EE and PA factors representing whether one would expect higher or

3   lower scores based upon this DP level. Similarly, Model D considers the general factor to be

4   PA, with the EE and DP factors indicating whether one would expect higher or lower scores

5   based upon this PA level. Given the original conceptualisation of the MBI-HSS as a tripartite

6   phenomenon, it was important to examine the performance of these three distinct *S-1*

7   specifications. Eid and colleagues (2017) note model fit can change when the reference

8   domain changes as the selection of a different reference domain represents potential item

9   heterogeneity in a different way. An alternative is to specify the less restrictive $S \cdot I$-1 model to

10   represent item heterogeneity more generally.

11   For the $S \cdot I$-1 model (Model E), item 8 (*feel burned out*) was selected as the reference

12   indicator. Eid and colleagues (2017) advocate this reference indicator be a 'gold-standard'

13   indicator for the general factor. Mészáros et al., (2014) found item 8 to be the strongest

14   loading item onto their *'global burnout'* general factor. Furthermore, West, Dyrbye, Satele,

15   Sloan and Shanafelt (2012) found that, when used as a single indicator, item 8 revealed

16   strong and consistent relationships with outcomes such as turnover intentions, relative to the

17   use of the full MBI-HSS scale, in a physician sample. An examination of factor loadings for

18   the original MBI-HSS (Model A) in the test sample indicated that item 8 had both the highest

19   loading and squared multiple correlation. Eid et al., (2017) state the $S \cdot I$-1 model should be

20   applied when the inclusion of the additional specific factor makes practical sense. Emotional

21   exhaustion is considered a key aspect of Leiter's (2008) Two Process Model of Burnout,

22   hypothesized to develop from a chronic mismatch in job demands and resources. Therefore,

23   the application of an $S \cdot I$-1 model with an EE specific domain was warranted. Considering this

24   evidence, and the item phrasing, item 8 was selected as the most appropriate reference item.

1   Analyses were conducted using the WLSMV estimator with THETA parameterisation

2   (Muthén & Muthén, 2018). Goodness of fit was assessed using chi-square (χ^2) test statistic,

3   the comparative fit index (CFI) and the Tucker Lewis index (TLI). A non-significant chi-

4   square, CFI and TFI >.95 indicate good model fit (Hu & Bentler, 1999). Furthermore, a root

5   mean square error of approximation (RMSEA) <.06 and a standardised root mean square

6   residual (SRMR) <.08 indicate acceptable model fit (Hu & Bentler, 1999). As the test sample

7   size exceeded those recommended for confirmatory factor analyses (Comrey & Lee, 1992),

8   the sample was deemed sufficiently powered and formal sample size calculations were not

9   conducted. The data examined are available on request and are not publicly available so as

10   not to compromise participant or organizational identification.

11   Following the examination of the five alternative CFA models (Figure 2) in both test

12   and validation samples, exploratory structural equation models (ESEM) versions of models

13   A-E were specified using the target rotation function. Thus, indicators could cross-load onto

14   the other reference domains, with these loadings targeted to approximate zero.

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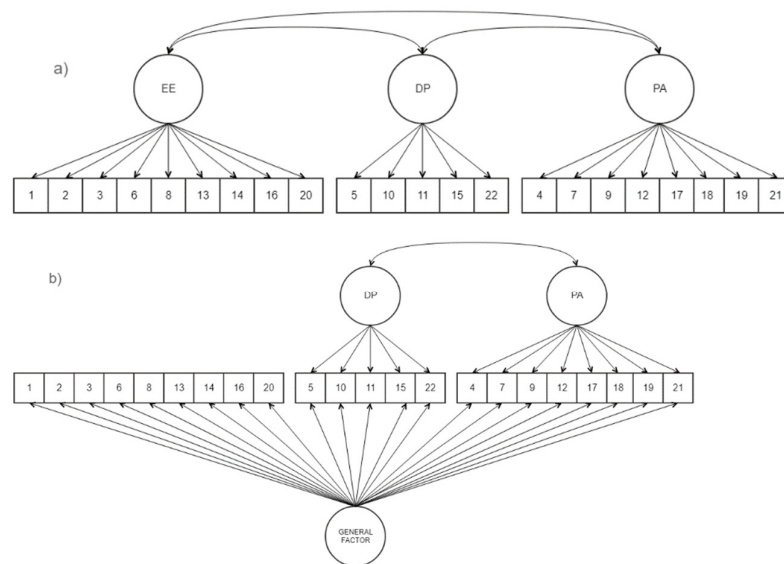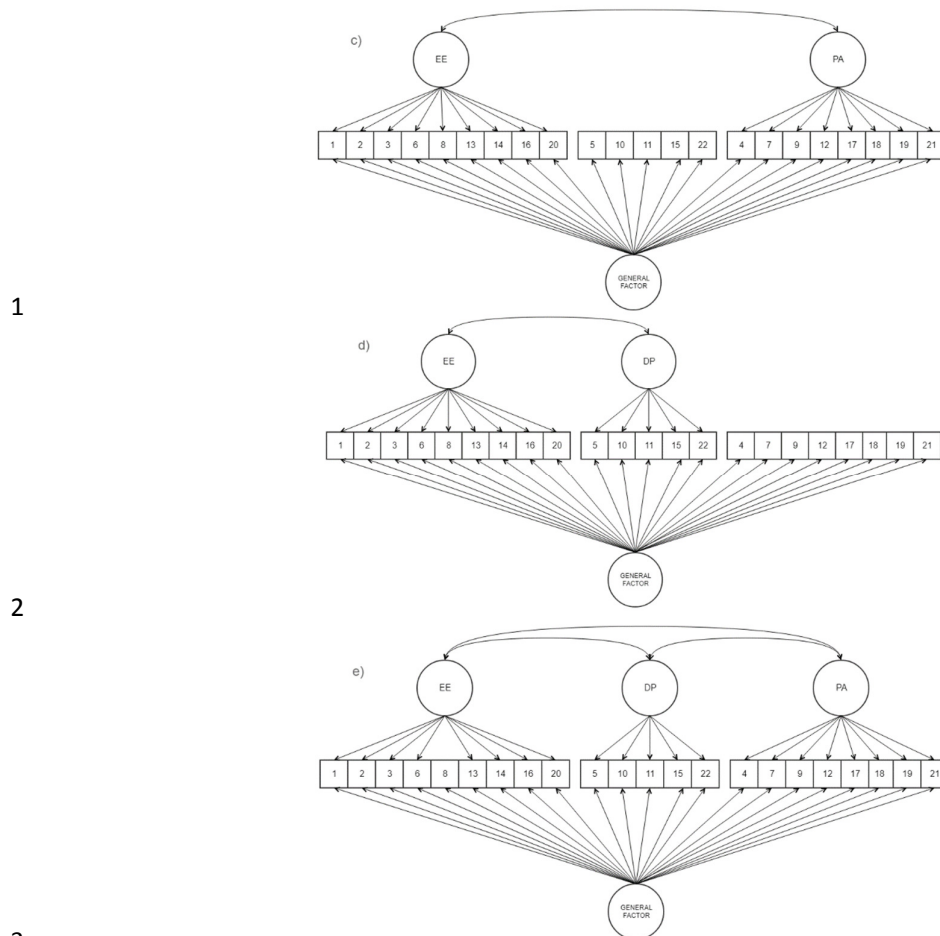
Figure 2: Alternative factor models examined where a) Maslach et al., (1996); b) S-1 with

EE as the reference domain; c) S-1 with DP as the reference domain; d) S-1 with PA as the

reference domain; e) S·I-1 with item 8 as the reference item.

Results

CFA models

The chi-square values for all CFA models were statistically significant due to the

large sample size (Tanaka, 1987). Accordingly, model fit was examined using a variety of fit

statistics (Table 2). In order to achieve model identification, factor loadings for four items

(items 1, 2, 3 and 6) on the specific factor were fixed to 1 in Model E. Eid et al., (2017)

previously reported model identification issues when specifying the *S·I-1* model which were

resolved by fixing the item loadings onto the specific factor to 1. As we encountered similar

1   problems these loadings were fixed in a sequential manner until model identification was

2   achieved.

3   All models showed acceptable fit with respect to CFI and SRMR indices in both

4   samples. The RMSEA values and 90% confidence intervals for the CFA models did not

5   indicate an acceptable fit. However, improved values were obtained within the validation

6   sample. Whilst the utility of threshold values for fit indices has been debated, it has been

7   argued an element of human judgement must be incorporated when assessing fit (Chen,

8   Curran, Bollen, Kirby & Paxton, 2008). Thus, model fit indices were examined in

9   conjunction with the standardised factor loadings and modification indices, as well as a

10   consideration of their theoretical underpinnings.

11   The bifactor models displayed anomalous loading patterns for PA items 4 and 21 (see

12   Electronic Supplementary Material). In Model B item 4 loaded positively onto the general

13   factor, whereas all other PA items loaded negatively. Personal accomplishment items are

14   positively worded and were thus expected to load negatively onto g when specified using the

15   negatively worded EE as the reference domain. Furthermore, item 4 did not load significantly

16   onto g in the validation sample for Models B and E, or in either sample when Model C was

17   specified. Item 21 did not load onto g when Model B was specified in the test sample, nor

18   did it load significantly onto g when Model E was specified in either sample. In both samples

19   moderate intercorrelations between the specific factors were observed for Models D and E.

20   Of the CFA models the bifactor specifications showed superior fit indices; Model E

21   possessed the highest CFI and lowest RMSEA in both samples. As Model A is nested within

22   Model E, a chi-square difference test was conducted and indicated the correlated first-order

23   factor specification provided significantly worse fit to the test ($\Delta\chi^2(18, N = 1257) = 759.88$, p

24   $< .001$) and validation ($\Delta\chi^2(18, N = 162) = 64.50$, $p < .001$) samples.

1   *Table 2*

2   *Comparative fit indices of alternative models of the MBI-HSS in both test and validation samples*

Model	Test sample (N = 1257)							Validation sample (N = 162)						
	χ^2	df	p	CFI	TLI	RMSEA	SRMR	χ^2	df	p	CFI	TLI	RMSEA	SRMR
						[90% CI]							[90% CI]	
CFA-A	3210.98	206	<.001	.903	.891	.108 [.104, .111]	.072	413.03	206	<.001	.942	.935	.079 [.068, .090]	.070
CFA-B	2725.24	195	<.001	.918	.903	.102 [.098, .105]	.054	371.73	195	<.001	.950	.941	.075 [.063, .086]	.058
CFA-C	2421.45	191	<.001	.928	.913	.096 [.093, .100]	.053	388.20	191	<.001	.944	.933	.080 [.068, .091]	.062
CFA-D	2856.46	194	<.001	.914	.897	.104 [.101, .108]	.064	374.33	194	<.001	.949	.939	.076 [.064, .087]	.062
CFA-E	2070.52	188	<.001	.939	.925	.089 [.086, .093]	.046	346.71	188	<.001	.955	.945	.072 [.060, .084]	.054
ESEM-A	1846.52	168	<.001	.946	.925	.089 [.086, .093]	.032	282.18	168	<.001	.968	.956	.065 [.051, .078]	.042
ESEM-B	2709.05	184	<.001	.918	.897	.104 [.101, .108]	.050	338.58	184	<.001	.956	.945	.072 [.060, .084]	.053
ESEM-C	1748.80	176	<.001	.949	.933	.084 [.081, .088]	.038	333.98	176	<.001	.955	.942	.074 [.062, .087]	.053
ESEM-E	1112.93	149	<.001	.969	.952	.072 [.068, .076]	.026	227.89	149	<.001	.978	.966	.057 [.042, .072]	.037

3   *Note*: χ^2: chi square test statistic; *df*: degrees of freedom; CFI: comparative fit index; TLI: Tucker Lewis index; RMSEA: root-mean-square error of approximation; CI:

4   confidence interval; SRMR: standardised root-mean-square residual; ESEM: exploratory structural equation model; no convergence was obtained for ESEM model D

1   *Exploratory Structural Equation Modeling (ESEM)*

2   Despite Model E showing acceptable to good fit in the test and validation samples,

3   respectively, moderate factor intercorrelations (see Electronic Supplementary Material)

4   suggested that this may not be the best fitting model for the MBI-HSS. Thus, all five models

5   were re-specified as ESEM models. Model fit indices for ESEM specifications can also be

6   observed in Table 2. The bifactor-ESEM Model E was selected as the final model, as it

7   demonstrated the best CFI, RMSEA and SRMR values in both samples. Furthermore, the

8   decreased factor intercorrelations observed further supported the selection of the bifactor-

9   ESEM Model E as the best fitting model. Standardised factor loadings and factor correlations

10   for Model E-ESEM can be observed in Table 3. Non-significant loadings onto the general

11   factor were observed for items 21 and 4 in the test and validation samples, respectively.

12   *Measurement Invariance*

13   Model identification could not be obtained for bifactor-ESEM Model E when

14   examining configural invariance in the test sample. An examination of the bifactor-ESEM

15   Model E for males and females separately showed good fit for both males and females,

16   however, differences in loading patterns on the *g* factor were observed (see Electronic

17   Supplementary Material). Thus, gender effects were examined using a Multiple Indicators,

18   Multiple Causes Model (MIMIC). No significant association was observed between gender

19   and the latent factors of the bifactor-ESEM Model E; however, the modification indices

20   suggested some misspecification. The inclusion of paths between gender and the items

21   directly revealed significant associations for items 12 ($\beta = -.119$, $p < .001$) and 21 ($\beta = -.098$,

22   $p = .001$), controlling for the effects of the latent factors, χ^2 (165, $N = 1229$) = 1073.84, $p <$

23   .001, CFI = .971, RMSEA = .067 [90% CI .063, .071]).

1 *Table 3*

2 *Standardised Factor Loadings and Correlations for the S·I-1 bifactor-ESEM model*

	Test sample (N=1257)				Validation sample (N=162)			
	GB	EE	DP	PA	GB	EE	DP	PA
MB1	.866**	-.153**	.026	.060*	.825**	.279**	.003	.038
MB2	.853**	-.214**	.037	.010	.835**	.307**	-.054	-.085
MB3	.828**	-.041	-.006	-.042	.765**	.082	-.074	-.220**
MB4	.115*	-.041	-.178**	.339**	.063	.082	-.203*	.301**
MB5	.316**	.025	.552**	-.097**	.434**	-.100	.464**	-.049
MB6	.605**	.528**	.092**	.009	.697**	-.274*	-.061	-.206*
MB7	-.146**	.093*	-.102**	.635**	-.151	.269**	-.237**	.548**
MB8	.896**	N/a	N/a	N/a	.865**	N/a	N/a	N/a
MB9	-.173**	.152**	-.024	.812**	-.210*	-.093	-.145	.659**
MB10	.385**	-.033	.772**	.031	.465**	.018	.805**	-.020
MB11	.428**	-.018	.705**	.075**	.440**	.126*	.619**	-.033
MB12	-.475**	-.012	.112**	.374**	-.334**	-.214**	-.135	.429**
MB13	.718**	-.048	.075*	-.048	.709**	.068	.046	-.123
MB14	.673**	-.048	.097*	.083*	.553**	.085	.166*	.050
MB15	.254**	.146**	.527**	-.116**	.211*	-.159*	.539**	-.155
MB16	.546**	.629**	.041	.029	.650**	-.215*	.010	-.174*
MB17	-.117**	-.159**	-.029	.518**	-.224*	.210*	-.224*	.487**
MB18	-.207**	-.136**	.110**	.585**	-.189*	-.121	.017	.651**
MB19	-.192**	.048*	.037	.777**	-.209*	.180*	.217*	.869**
MB20	.845**	-.004	-.006	-.033	.776**	-.025	-.087	-.090
MB21	.009	-.079*	-.065	.480**	-.209*	.408**	.055	.438**
MB22	.345**	.029	.241**	-.090*	.566**	.149	.278**	-.144*
Correlations								
EE	N/a				N/a			
DP	N/a	.37**			N/a	-.22*		
PA	N/a	-.30**	-.29**		N/a	.13	-.36**	
ω^a	.894	.804	.768	.775	.886	.751	.754	.699
$\omega_H{}^b$	.608	.029	.319	.569	.670	.038	.287	.648

3 *Note:* GB: Global Burnout; EE: Emotional Exhaustion; DP: Depersonalisation; PA: Personal Accomplishment;
4 N/a: non-applicable; ω: McDonald's omega; a: omega subscale in the case of EE, DP and PA specific factors;
5 ω_H: omega hierarchical; b: omega hierarchical subscale in the case of EE, DP and PA specific factors; * $p < .05$;
6 ** $p < .001$

1   *Validity*

2   Correlations between the latent factors of bifactor-ESEM Model E and resilience,

3   modeled as a latent factor, indicated higher resilience was associated with lower global

4   burnout (r = -.32, p < .001, 90% CI -.45, -.19), higher personal accomplishment (r = .53, p <

5   .001, 90% CI .40, .66) and higher emotional exhaustion (r = .68, p = .002, 90% CI .31, 1.04).

6   No significant correlation was observed between resilience and depersonalisation (r = -.11, p

7   = .292, 90% CI -.29, .06).

8   **Discussion**

9   The frequent identification of undesirable loading patterns for the MBI-HSS led

10   researchers to respond by either eliminating cross-loaded items (Kim & Ji, 2009; Stalker et

11   al., 2008; Yadama & Drake, 1995) or to specify a bifactor model (Mészáros et al., 2014).

12   However, Eid et al., (2017) argue that Mészáros and colleagues' (2014) bifactor specification

13   violates Stochastic Measurement Theory (SMT), calling their conclusions into question. The

14   results show that dimensionality within the MBI-HSS is best represented by a bifactor-ESEM

15   specified in accordance with SMT. The *S·I*-1 specification using item 8 (*feel burned out)* as

16   the reference item was the better performing CFA model and when specified within an ESEM

17   framework provided the best fit to both test and validation samples.

18   Eid et al., (2017) argue that the absence of at least one significant loading onto the

19   general factor was an artefact of violations of SMT by traditional bifactor specifications.

20   Here, we have shown that anomalous loading patterns for item 4 of MBI-HSS persist, despite

21   the use of SMT-compatible bifactor specifications. Stalker and colleagues (2008) argue social

22   worker responses to this item may diverge from their response pattern to other PA items.

23   Differences in life experiences may mean social workers appraise themselves as incapable of

24   truly understanding their clients' feelings, if they have not experienced similar life

1   challenges. Similarly, social workers may display empathy, indicating an ability to

2   understand their clients, and yet still experience a sense of inefficacy.

3   Few existing studies examining alternative MBI-HSS specifications consider

4   relationships with external criteria. Here, we show the bifactor-ESEM displayed correlations

5   with resilience in the expected direction, supporting the external validity of our model.

6   Higher resilience was associated with higher levels of personal accomplishment and lower

7   global burnout. Taku (2014) found higher resilience predictive of lower emotional exhaustion

8   and higher personal accomplishment among physicians, with no association with

9   depersonalisation identified. However, we observed an unexpected positive association with

10   the emotional exhaustion reference domain, dominated by items 6 (*people work a strain)* and

11   16 (*people work too stressful).* We posit that high levels of resilience displayed by social

12   workers does not prevent them from recognising the emotionally draining nature of their role.

13   The present findings must be interpreted in light of several limitations. A self-selected

14   sample may serve to inflate burnout levels through greater survey engagement. Alternatively,

15   those who experienced burnout may have already exited the profession. Furthermore, the

16   analysis presented here did not offer the opportunity to examine the discriminant and

17   predictive validity of the bifactor-ESEM Model E. Additionally, measurement invariance

18   could not be examined due to model identification issues. Whilst some gender differences in

19   item functioning were observed, further research is required to determine whether a bifactor-

20   ESEM approach is equivalent for males and females. Whilst the gender imbalance observed

21   reflects the natural skew reported within the profession (General Social Care Council, 2010),

22   males were underrepresented in both test and validation samples.

23   To date, the three-dimensional conceptualisation of burnout has dominated the

24   literature. Reconceptualising burnout as a general phenomenon, with additional specific

1   factors that explain additional variance in the experience, may alter what we already

2   understand about burnout and associated correlates. Future research is required to examine

3   how this novel bifactor structure integrates with correlates identified to date. In practice,

4   examining the relationships between burnout and potential covariates will require the

5   incorporation of structural equation modeling techniques and not merely score computation,

6   which may be beyond the scope of some practitioners.

7   The present study is unique as it is the first to examine the factorial validity of the

8   MBI-HSS in UK social workers. The study extends the existing literature by confirming that

9   when SMT is considered, the underlying structure of the MBI-HSS remains that of a bifactor

10   specification. Furthermore, the study highlights that bifactor-ESEM provides a better

11   framework within which to examine the latent structure of MBI-HSS. Furthermore, the study

12   highlights the importance of examining the factor structure of the MBI-HSS prior to

13   examining relationships with related constructs. An accurate identification of burnout is

14   critical to develop interventions to assuage the impact on the workforce.

15

16   **Electronic Supplementary Material**

17   **ESM 1. Appendices 1-10 (.doc)**

18   The appendices show additional tables of standardised factor loadings and correlations for

19   tested models.

20

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