



Psychometric Assessment of the Mental Health Continuum-Short Form in Athletes: A Bifactor Modeling Approach

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1 **Title page**

2 **Title:** Psychometric Assessment of the Mental Health Continuum-Short Form in Athletes: a
3 Bi-factor Modelling Approach.

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16 **Keywords:** well-being; measurement; mental illness; ill-being; methods.
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18

19 **Abstract**

20 **Aim:** A recent mental health in sport consensus statement (Breslin et al., 2019) advocates

21 Keyes (2002) two-continua model with an associated Mental Health Continuum (MHC)

22 instrument to assess mental health in athletes. However, there remains statistically

23 inconsistent usage of the MHC in athletes, so further exploration of the MHC's psychometric
24 factors is required.

25 **Methods:** Athletes ($N=1,097$) aged 32.63 (SD =11.16) comprising 603 females (55.7%) and

26 478 males (44.3%), completed the 14-item MHC-short form (MHC-SF), alongside validated

27 measures of anxiety and depression. Five confirmatory factor analytic (CFA) and bi-factor

28 models were developed based on extant research and theory.

29 **Results:** Overall, first-order models did not fit the data, but a bi-factor structure with a
30 ‘general’ positive mental health factor, and three specific factors (‘Hedonic well-being’,
31 ‘Social well-being’ and ‘Psychological well-being’) fitted the data well and was deemed the
32 superior model.

33 **Conclusions:** A bi-factor model of the MHC-SF is recommended comprising a composite
34 score alongside specific factors of hedonic, social and psychological well-being.

35 **Keywords:** Well-being; psychology; confirmatory factor analysis; validity; sport.

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39 Psychometric Assessment of the Mental Health Continuum-Short Form in Athletes: a Bi-
40 factor Modelling Approach.

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42 In response to the preponderance and legacy of the illness-based model of mental health,
43 Keyes (2002) presented a theory to reclaim ‘mental health’ as a positive construct
44 characterised by ‘flourishing’. Keyes (2005) later examined axioms of multidimensional
45 mental health, presenting a two continua model wherein mental health and mental illness
46 coexist as two distinct, but correlated, unipolar dimensions. To this end, Keyes et al. (2008)
47 considered ‘flourishing’ as a diagnosable presence of positive mental health, with
48 ‘languishing’ as the absence of positive mental health. While the determinantal societal
49 effects of mental illness (e.g., depression, anxiety) have been publicly understood and of clear
50 significance to policy makers for generations (Jones, 2013), it is only within the last fifteen
51 years that positive mental health (or well-being) has been considered an essential aspect of
52 public health (Huppert, 2009). Indeed, educational success, living in a safe neighbourhood,
53 family support, and economic prosperity correlate with positive mental health (United
54 Nations, 2015).

55 Within the context of competitive sport, mental health is a rapidly emerging research
56 field, to the extent that global sporting bodies (e.g., The International Olympic Committee
57 [IOC]), national sport organisations, and researchers have recently developed action plans or
58 consensus statements to safeguard athlete mental health (Vella & Swann, 2021). There are an
59 abundance of elite athlete mental health consensus statements (e.g., Henriksen et al., 2020),
60 including by the IOC (Reardon et al., 2019). Mirroring the messages of, and responding to,
61 recommendations among consensus statements for elite athlete’s mental health, the IOC
62 recently developed the Sport Mental Health Assessment Tool 1 (SMHAT-1) and Sport

63 Mental Health Recognition Tool 1 (SMHRT-1) (Goutteborge et al., 2021). Notably, both
64 measures and the field at large remain focused on mental illness symptoms and concepts.
65 One international consensus statement focused on non-elite athletes (i.e., Breslin et al., 2019),
66 who comprise the vast majority of sporting participants (Vella & Swann, 2021). As such, it
67 was and remains pertinent that Breslin et al. (2019) recommended that all competitive
68 athletes' mental health be viewed from Keyes' (2002) theoretical perspective. Indeed, the
69 view put forward by Breslin et al. (2019) and others (e.g., Uphill, Sly & Swain, 2016) is that
70 Keyes' (2002) model is theoretically robust, and reflective of a multidimensional mental
71 health construct comprising well-being, broadening the existing dominant focus on mental
72 illness.

73 Indeed, in a review of existing well-being measures in sport Giles et al. (2020) argued
74 that researchers have typically employed proxy indicators of well-being (e.g., life
75 satisfaction, affect, subjective vitality) without sufficient theoretical basis. A lack of
76 theoretically guided research ultimately hinders progress on understanding the correlates that
77 influence an athlete's overall mental health (Lundqvist & Sandin, 2014). As such, there is
78 need for theoretically derived, valid measurement tools to screen athletes' mental health as
79 conceptualised by Keyes (2002; 2005) two continua model (Uphill, Sly & Swain, 2016).
80 Having such instruments is crucial for assessing types of suitable care for athletes,
81 intervention effectiveness, and providing policymakers with valid and reliable data (Breslin et
82 al., 2017; Breslin & Leavey, 2019; Giles et al., 2020).

83 Keyes' (2002; 2005) Mental Health Continuum (MHC) instrument was constructed
84 via philosophical traditions and contemporary theories (e.g., Diener & Emmons, 1984; Ryan
85 & Deci, 2000). The mental health (or well-being) continua derives its structure and items
86 from hedonic (i.e., Diener's subjective well-being), social (i.e., Keyes' social functioning),
87 and eudemonic (i.e., Ryff, Self-Determination Theory) theories. The mental illness continua

88 include latent measures such as major depressive disorder, panic, generalized anxiety disorder
89 and alcohol dependence as defined by the Diagnostic and Statistical Manual of Mental
90 Disorders. From Keyes' (2005) perspective, a number of possible mental health profiles
91 emerge, for example an athlete could simultaneously experience positive mental health along
92 with mental illness. Contrastingly, an athlete could be free from mental illness, but
93 experience low levels of mental health (i.e., languishing).

94 Keyes (2002; 2005) long-form MHC instrument comprised of 42-items measuring
95 three factors of hedonic (i.e., positive affective states, life satisfaction), eudemonic (e.g.,
96 psychological functioning, sense of purpose), and social (i.e., relationships, integration)
97 mental health. However, most researchers opt for the Mental Health Continuum-Short Form
98 (MHCSF; Keyes et al., 2008), likely due to its retention of psychometric validity, whilst
99 obtaining practical ease and lessening participant time burden (Jovanović, 2015). The 14-item
100 MHC-SF includes three items (two for positive emotions, and one for life satisfaction) in the
101 hedonic construct; six items for the eudemonic (or psychological) construct; and, five items
102 for the social construct. From its inception, the MHC-SF is a leading mental health
103 instrument in public mental health research (Longo et al., 2020), including more recent
104 epidemiological studies among athletes (McGivern, Shannon & Breslin, 2021).

105 However, Jovanović (2015) initially questioned the widescale adoption of the default
106 three-dimensional structure of MHC-SF. Indeed, several studies have reported either
107 marginally acceptable (Joshani & Jovanović, 2017) or unacceptable (Jovanović, 2015)
108 model fit indices for a first-order three-factor solution. Moreover, among the studies testing
109 the measurement properties of the MHC-SF with athletes, one study among adolescent non-
110 elite athletes found an adequate fit for the three-factor model only following the removal of
111 three items (Salama-Younes, 2011); another study solely among collegiate athletes revealed
112 an unacceptable fit (Foster & Chow, 2019). Indeed, despite any prevailing statistical

113 evidence, several athlete mental studies have treated the instrument as a composite score
114 suggesting a unitary construct (Vella et al., 2020; McGivern, Shannon & Breslin, 2021). Such
115 limited sample compositions and issues of model misfit require solutions and clarity, as an
116 instrument's validity informs clinical practice, research, and policy decisions (Park, Han &
117 Cho, 2011; Fried, 2017).

118 Confirmatory Factor Analysis (CFA) encompasses specified correlations between
119 observed questionnaire items and latent variable(s). Through inspection of conventional fit
120 statistics, researchers can determine the strength of evidence for a psychometric instrument's
121 ability to capture its underlying 'true' or 'natural' construct(s) (Schreiber et al., 2006).
122 Specifically, using CFA researchers can assess competing CFA models that include
123 unidimensional (i.e., one underlying construct) and first order (i.e., correlated sub-
124 dimensions) structures (Jackson et al., 2009). Furthermore, confirmatory bi-factor modelling
125 (CBFA) permits items to correlate with a general factor (e.g., mental health) alongside sub-
126 dimensions, or specific factors (Reise, 2012), with the caveat that additional bi-factor specific
127 calculations are warranted alongside conventional fit statistics (Rodriguez, Reise & Haviland,
128 2016). It has been proposed that a sound measure should display nomological validity, which
129 pertains to the correlation between the measured construct and further constructs within the
130 same theory (e.g., Hagger & Chatzisarantis, 2009), for example, Keyes' (2002) hypothesised
131 correlation between mental well-being and mental illness.

132 In view of the above limited evidence for the default three-factor MHC-SF, several
133 authors re-specified the structure among general populations, and tested alternative CFA
134 models including CBFA (Jovanović, 2015). Several studies replicated Jovanović's (2015)
135 methods revealing that a bi-factor model (comprising one general mental health, and three
136 specific factors) to be superior (see, De Bruin and Du Plessis 2015; Hides et al. 2016;
137 Jovanovic' 2015). It is methodologically advised to test competing psychometric

138 measurement models among diverse, representative, samples (Park, Han & Cho, 2011). Yet,
139 to our knowledge, no such studies have assessed a CBFA of the MHC-SF in athletes despite
140 the measure's widescale and growing use with athletes. Given Breslin et al.'s (2019)
141 consensus statement advocated Keyes' (2002) theory, and limited model fit evidence exists
142 for the MHC-SF among narrow athlete samples (i.e., Salama-Younes, 2011; Foster & Chow,
143 2019), there is a need for a more comprehensive psychometric assessment of the MHC-SF
144 among a diverse athletic sample.

145 Hence, the aim of this study was to assess competing CFA and CBFA measurement
146 models of the MHC-SF, and its psychometric properties (i.e., nomological validity) across a
147 large, demographically diverse sample of athletes representing a range of competitive sports
148 (e.g., co-active team sports, individual athletic sports) and levels (e.g., elite, semi-athlete,
149 amateur). We specified measurement models as outlined in Figure 1 that were based on
150 extant research (Jovanović, 2015) and consistent with Keyes' (2002) conceptualisation of
151 mental health and mental illness.

152

153

Place Figure 1 here

Methods

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155

Study Design, Recruitment and Participants

156 Ethical approval was granted by [REDACTED] Research Ethics Filter Committee. The
157 Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement
158 was used in the design of the current cross-sectional survey of athletes. Inclusion criteria was
159 based on informed consent, being ≥ 18 years old, and participants confirming their athlete
160 status using a widely used screening item (e.g., Shannon et al., 2019; Breslin et al., 2019)
161 based on the definition of sport: ‘are you an athlete involved in a structured, competitive
162 physical activity?’ (Rejeski & Brawley, 1996).

163 Recruitment involved a snowball sampling method wherein an encrypted online
164 questionnaire link produced through SurveyMonkey software was distributed to a range of
165 Twitter and social media outlets, sports club secretaries, and sporting organisations. Several
166 sports organisations responded and distributed online links accordingly to followers and
167 subscribers. Data derived from online psychometric collection methods have been shown to
168 yield sound psychometric reliability and validity estimates in comparison with paper-based
169 surveys, and show an added benefit of reducing attrition and false/missing responses
170 (Lonsdale et al, 2006). Data was collected from January 2019 to March 2021 and took
171 approximately ten minutes to complete. Demographic questions (i.e., gender, age, country),
172 and sporting characteristics (i.e., individual or team sport) were collected.

173 Subsequently, data was collected from 1,097 participants comprising 603 females
174 (55.7%) and 478 males (44.2%), with one participant (0.1%) indicating ‘other’ for gender.
175 The mean age of participants was 32.63 (SD =11.16) with most identifying as Irish (44.2%),
176 followed by Canadian (27.4%), British (19.3%) and others (e.g., American, Australian). The
177 largest sport represented among the athletes was equestrian (34.3%), followed by rugby
178 (28.7%), hockey (5.3%) and others (e.g., Running, Gaelic sports). Further, 53.3% of the

179 sample participated in individual sports, whereas 46.8% took part in coactive team sports.
180 The vast majority (79.7%) of the participants classified themselves as non-elite (e.g.,
181 amateur, local/community leagues) while 13.6% were elite (i.e., professional, international),
182 and 6.7% were semi-elite (e.g., semi-professional). Among those who responded to an item
183 regarding mental illness history ($n= 891$, 81.2%), 51.9% indicated they had not experienced
184 mental illness, 39.6% had experienced mental illness, and 8.5% answered that they did not
185 know or were unsure.

186 **2.2 Outcome Measures**

187 *Mental Health Continuum- Short Form (MHC-SF)*

188 Respondents completed the Mental Health Continuum - Short Form (MHC-SF: Keyes et al.,
189 2008), which assesses the positive mental health dimension of Keyes (2005) two-continua
190 model. As described earlier, the 14-item scale is theorised (Keyes, 2002) to derive hedonic
191 (i.e., items 1-3), social (i.e., items 4-8) and psychological (i.e., items 9-14) well-being
192 dimensions. The recall period for the MHC-SF is ‘over the past month’, wherein respondents
193 rate the frequency of every feeling (e.g., happy) or experience (e.g., that you had warm and
194 trusting relationships) on a 6-point Likert scale ranging from ‘Never’ (0) to ‘Every day’ (5).
195 Total scores can range from 0-70, with higher scores indicating positive mental health. High
196 comprehension, internal validity and cross-cultural reliability has been shown for the MHC-
197 SF (Lamers et al., 2011). Consistent with previous research (Lamers et al., 2011; Ferentinos
198 et al., 2019), the scale showed high internal consistency (Cronbach’s $\alpha=.94$),

199 *Depression*

200 Depression symptoms were assessed using the eight-item version of The Patient Health
201 Questionnaire (PHQ-8: Kroenke et al., 2009). The PHQ-8 is a well-established diagnostic and
202 severity measure for major depressive disorders in large clinical and non-clinical samples

203 (Razykov, Ziegelstein, Whooley & Thombs, 2012), and has demonstrated sound
204 psychometric properties (Wu et al., 2019). Respondents indicated the number of days in the
205 past two weeks in which they experienced a particular depressive symptom (e.g., anhedonia,
206 hopelessness) on a 4-point Likert scale, ranging from ‘Not at all’ (0) to ‘Nearly every day’
207 (3). Possible scores range from 0-24, with higher scores representing greater severity of
208 depression. Cronbach’s $\alpha=.87$ in the present sample.

209 *Anxiety*

210 The seven-item Generalized Anxiety Disorder (GAD-7: Spitzer et al., 2006) scale was used
211 as a measure of anxiety. Using a two-week recall period, respondents indicate the degree to
212 which they have been bothered by anxious feelings (e.g., restlessness, afraid as if something
213 might happen) with a 4-point Likert scale, ranging from ‘Not at all’ (0) to ‘Nearly every day’
214 (3). Sound psychometric properties and diagnostic efficacy have been shown for the GAD-7
215 among large clinical and non-clinical samples (Löwe et al., 2008), including online study
216 methodologies (Donker et al., 2011). GAD-7 scores range from 0-21, with higher scores
217 representing increased anxiety symptoms. Cronbach’s $\alpha=.92$ in the present sample.

218 *Resilience*

219 Resilience was measured through the six-item Brief Resilience Scale (BRS) (Smith et al.,
220 2008). Questions were anchored in a 5-point Likert scale (1-strongly disagree to 5- strongly
221 agree) and inquired on “bounce-back-ability” during adversity (e.g., “I tend to bounce back
222 quickly after hard times”). Scores are averaged and range from 0 to 5, with higher scores
223 reflecting stronger resilience. Cross-cultural reliability and validity have been demonstrated
224 for the BRS (Smith et al., 2008; de Holanda Coelho, Hanel, Medeiros Cavalcanti, Teixeira
225 Rezende & Veloso Gouveia, 2016). Cronbach’s $\alpha=.57$ in the present sample.

226 *Data Analysis*

227 Prior to main analyses, data was inspected for missing responses and outliers. As 4.1% of
228 data was missing on the MHC-SF, Little's MCAR test was calculated and revealed data was
229 missing completely at random ($p > .05$). Missing data was therefore estimated using multiple
230 imputation function in the SPSS (version 25). Data was fully labelled and exported to AMOS
231 (version 24) to assess the latent structure of the 14-item MHC-SF.

232 Five competing confirmatory factor analysis (CFA) and confirmatory bifactor
233 analysis (BCFA) models were specified based on model iterations by Jovanović (2015) (see
234 Figure 1 for a visual representation) and estimated using robust maximum likelihood
235 estimation (see Table 1). Models included CFA on a unidimensional structure (Model 1); a
236 first order with two correlated factors (Model 2); a first order model with three correlated
237 factors (Model 3); a BCFA comprising a general factor and two orthogonal specific factors
238 (Model 4), and lastly; a BCFA comprising a general factor and three orthogonal specific
239 factors (Model 5).

240 The performance of the competing measurement models was assessed through
241 comparison of multiple recommended goodness-of-fit indices (Hu & Bentler, 1999). The
242 Chi-Square [χ^2] goodness-of-fit index was reported, however given that χ^2 is sensitive to large
243 sample sizes (Bentler, 1990) we approached this value with caution. The Normed Fit Index
244 (NFI) Tucker-Lewis Index (TLI) and Comparative Fit Index (CFI) were reported, and values
245 of $>.90$ or $>.95$ were considered as acceptable or good-to-excellent model fit, respectively.
246 The root mean square error of approximation (RMSEA) values were calculated, with a cut-
247 off point of $.08$ or below considered acceptable. Additionally, the Akaike Information
248 Criterion (AIC) and Bayesian Information Criterion (BIC) were assessed. Improved model
249 performance was observed when AIC and BIC values were lower in comparison to other
250 models. Lastly, the recommendations of Comrey and Lee (1992) were adopted for
251 determining the strength of factor loadings (i.e., $<.30$ = poor; $>.45$ = fair; $>.55$ =good; $>.63$ =

252 very good, and; $>.71$ = excellent). Models were tested with 5000 Bollen-Stine bootstraps to
253 improve the accuracy of model parameters (Byrne, 2001).

254 In the case where the bi-factor model was considered the ‘best’ fit, further assessment
255 of the general and specific factors is required (Rodriguez, Reise & Haviland, 2016) so
256 supplementary BCFA fit statistics were calculated using Dueber’s (2017) software.
257 Specifically, omega reliability (ω ; i.e., proportion of common item variance explained by the
258 general and specific factors), omega hierarchical (ω_H ; i.e., proportion of variance within the
259 items attributable to the general or specific factors, controlling for the specific and general
260 factor), relative omega (ω_R : i.e., proportion of variance attributable to the general factor
261 independent of the specific factors, and specific factors independent of the general factor),
262 and index H (i.e., how a set of items represents a latent variable, and the likelihood of that
263 latent variable replicating across studies) were calculated. Omega coefficients and index H
264 values range from 0-1, and values $>.80$ reflect satisfactory reliability and replicability
265 (Rodriguez et al., 2016). We also reported the item explained common variance (I-ECV),
266 which reflects the extent to which an item's responses are accounted for by variation on the
267 latent general dimension alone. When I-ECV are $>.80$ or $.85$, a unidimensional structure for
268 the item is likely (Stucky & Edelen, 2015). A second table comprising the CBFA fit statistics
269 was produced, and a third table for the retained model describing the items and corresponding
270 factor loadings.

271 Nomological validity assessments were determined using hypotheses from Keyes
272 (2002) two-continua model of mental health. Based on Keyes (2002) theory we hypothesised
273 that the mental ill-being (i.e., depression and anxiety) outcomes would be inversely correlated
274 with the composite mental health score, whereas the BRS would be positively correlated.
275 Additionally, we inspected the correlations between the retained specific sub-factors and the
276 GAD-7, BRS and PHQ-8 whilst controlling for the composite score to determine their

277 relative external validity contribution. Pearson's Product-Moment Correlation (r) with alpha
278 significance set at $p < .05$ was calculated for two tables as per above, considering values of .0
279 - 0.3 as weak, .31 - .70 as moderate, and .71 and above as strong (Field, 2013).

280 **Results**

281 *CFA Fit Statistics*

282 Fit statistics for the competing measurement models are presented in Table 1. The χ^2 values
283 were all significant, likely due to the large sample size, and therefore did not lead to rejection
284 of the models (Tanaka, 1987). In Model 1, factor loadings were good-to-excellent ranging
285 from .57 (item 8) to .82 (item 14), all statistically significant ($p < .05$), and indicated some
286 supporting evidence for an overarching general mental health factor. However, all CFA fit
287 indices were below or above the recommended thresholds by Hu and Bentler (1999).
288 Similarly, in Model 2 all factor loadings were statistically significant, ranging from .58 (item
289 8) to .87 (item 2), and the covariation pathway between the two correlated factors was .84.
290 Whilst minor fit improvements were observed in comparison to Model 1, all fit statistics were
291 again below or above the recommended thresholds.

292 The default Model 3 on the other hand, comprising three correlated factors displayed
293 some acceptable fit statistics, namely NFI and CFI values of $> .90$, and marginally TLI (i.e.,
294 916). However, the RMSEA was above .08 (i.e., .088). AIC and BIC statistics continued to
295 decline, and all factor correlations were statistically significant, and elevated in comparison to
296 Models 1 and 2, ranging from .65 (item 8) to .87 (item 2). By conventional standards, Model
297 3 with three correlated factors showed marginally acceptable factorial validity.

298

299

300

301 **Table 1: Fit Statistics for the Competing CFA and CBFA Models Tested**

Model		χ^2	df	CFI	TLI	NFI	RMSEA	BIC	AIC
1	Unidimensional	1424.342	77	.852	.825	.845	.126	1620.351	1480.342
2	First-order (2-factor)	1000.864	76	.899	.879	.891	.105	1203.874	1058.864
3	First-order (3-factor)	695.751	74	.932	.916	.924	.088	912.761	757.751
4	Bi-factor (2-specific)	453.519	63	.957	.938	.951	.075	747.533	537.519
5*	Bifactor (3-specific)	336.829	63	.970	.957	.963	.063	630.843	420.829

302 **Note:** *Chosen as best fitting model

303

304 However, inspection of BCFA Models 4 and 5 showed further improvements
305 regarding CFA fit statistics and prediction of item variance. Model 4 comprising a general
306 positive mental health factor, and two specific factors of eudemonic and hedonic well-being,
307 yielded excellent NFI and CFI values of $>.95$, and an RMSEA value of $.075$ (see Table 1).
308 Additionally, AIC and BIC values continued to reduce, and all but one (i.e., item 4) of the
309 specific factor loadings were statistically significant, alongside all general factor loadings that
310 were statistically significant. Notably, however, the loadings of items 4-8 on the eudemonic
311 well-being (EW) specific factor were in a negative direction, some as large as $-.50$. Such
312 associations suggest that those items have a negative contribution to the factor and would
313 thus require subtraction in any model calculations. Significantly, items 4-8 constituted the
314 specific social well-being factor specified in Model 5, and given the inconsistencies in the
315 direction of associations with the general and specific factor items, suggested the possibility
316 of a distinct specific factor, as identified in Model 5.

317 To this end, the superior performance of Model 5 was evident in excellent fit statistics
318 (CFI = $.97$, TLI = $.96$, NFI = $.96$) values that outperformed the aforesaid models, as did the
319 RMSEA value at $.063$. AIC and BIC were at their lowest observed levels across all models.
320 Aside from item 4 (i.e., ‘that you had something important to contribute to society’) all

321 specific factor loadings were statistically significant, and in a positive direction, ranging from
 322 .10 (item 5) to .57 (item 8) (see Table 3). All general factor loadings were statistically
 323 significant, good-to-excellent, and ranged from .59 (item 10) to .82 (item 14).

324 *Bi-factor fit statistics*

325 When calculated in Dueber's (2017) bi-factor software, Model 5 showed, general and specific
 326 factor ω values of $>.80$ (see Table 2), and the majority (i.e., 9/ 14) of the I-ECV item values
 327 were $<.80$ rather than $>.80$ (see Table 3), suggesting some contribution of a multi-
 328 dimensional structure. However, ω_H and ω_R remained relatively low in relation to Rodriguez
 329 et al.'s (2017) benchmarks, as did H , suggesting a need for caution.

330 **Table 2:** Bi-factor indices calculator (Dueber, 2017) indicating reliability and construct
 331 replicability for the competing bi-factor models 4 and 5.

Factor	ω	ω_H	ω_R	H
General Factor	.947	.864	.913	.930
Hedonic well-being	.887	.227	.256	.416
Social well-being	.865	.184	.213	.532
Psychological well-being	.887	.177	.200	.457

332
 333 **Note:** GF= general factor; HW=hedonic well-being; EW=eudemonic well-being; SW=social well-
 334 being; PW=psychological well-being; ECV and PUC values are calculated at the model-level, rather
 335 than construct-level.

336
 337 Taken collectively, a somewhat contradictory picture emerged from the CFA and
 338 BCFA model analyses. That is, by conventional standards the only marginally acceptable
 339 CFA model included the three correlated factors (i.e., Model 3). Yet, despite the BCFA
 340 Model 5 outperforming all models (see Table 1), the bifactor fit statistics (see Table 2)
 341 showed a fairly strong overarching general mental health factor with relatively weak specific
 342 factors. Hence, we propose the retention of Model 5, using a cautious approach in the
 343 calculation of both general and subfactor scores.

344 In doing so, and applying Keyes (2002) figurative labels to the factors, Model 5
345 comprised a strong general 'positive mental health' factor, and three specific factors labelled:
346 'Hedonic' (items 1-3), 'Social (items 4-8) and 'Psychological' (items 9-14) well-being. As
347 visually illustrated in Figure 1, paths between items and the 'GF' symbol refer to loadings on
348 the general positive mental health construct, whereas item loadings onto HW (Hedonic Well-
349 Being), SW (Social Well-Being), and PW (Psychological Well-Being) represent the specific
350 factors.

351 *Nomological validity*

352 The correlation matrix for the retained model with the study outcomes is detailed in Table 4.
353 All correlations were statistically significant at $p < .001$. Relating specifically to the
354 correlations between MHC-SF factors (general and specific) and the study outcomes, r
355 ranged from .17 to -.57. The composite score representing the general well-being factor
356 showed moderate inverse correlations with depression ($r = -.57$) and anxiety ($r = -.31$), and a
357 weak positive correlation with resilience ($r = .22$). Table 4 also illustrates significant weak-
358 to-moderate correlations between specific subfactors and study outcomes with r ranging from
359 .17 to -.56.

360 Demonstrating some added contribution of retaining the bifactor model, correlations
361 between the specific sub-factors and study outcomes, independent of the controlled
362 association between the study outcomes and composite MHC-SF score, and while weak,
363 showed several incidences of statistical significance. Namely, and as identified in Table 5, the
364 HW factor was negatively associated with depression ($r = -.17$) and anxiety ($r = -.11$); SW
365 was surprisingly positively associated with depression ($r = .10$), and negatively associated
366 with resilience ($r = -.07$); and PW was positively associated with anxiety, albeit weakly ($r =$
367 .08).

368 **Table 3:** Retained bifactor model for MHC-SF, including instrument items, factor labels, and
 369 loadings with I-ECV values.

370

Item number and description	General factor loading	I-ECV	Specific factor	Specific factor loading	Item R^2
1. happy	.678*	.640 [∇]	HW	.509*	.718
2. interested in life	.755*	.762 [∇]	HW	.422*	.748
3. satisfied with life	.763*	.820 [^]	HW	.358*	.710
4. that you had something important to contribute to society	.803*	.00 [^]	SW	.014	.645
5. that you belonged to a community (like a social group, or your neighbourhood)	.705*	.979 [^]	SW	.104*	.509
6. that our society is a good place, or is becoming a better place, for all people	.602*	.603 [∇]	SW	.488*	.600
7. that people are basically good	.575*	.568 [∇]	SW	.501*	.582
8. that the way our society works makes sense to you	.536*	.470 [∇]	SW	.569*	.611
9. that you liked most parts of your personality	.684*	.726 [∇]	PW	.420*	.644
10. good at managing the responsibilities of your daily life	.591*	.643 [∇]	PW	.440*	.543
11. that you had warm and trusting relationships with others	.653*	.799 [∇]	PW	.328*	.535
12. that you had experiences that challenged you to grow and become a better person	.603*	.866 [^]	PW	.237*	.420
13. confident to think or express your own ideas and opinions	.667*	.762 [∇]	PW	.373*	.584
14. that your life has a sense of direction or meaning to it	.815*	.939 [^]	PW	.208*	.707

371 **Note:** *= statistically significant ($p < .05$); all R^2 values were statistically significant; HW = hedonic well-being specific factor; SW= social well-being specific factor; PW = psychological well-being specific factor; I-ECV=item-level explained common variance via the general factor; [^] = where I-ECV of >0.80 suggesting a reliable unidimensional structure for item; [∇] = where I-ECV of <0.80 suggesting some contribution of a multidimensional structure for item.

372 **Table 4:** Correlation matrix for the retained model factors and study outcomes.

Variables	1	2	3	4	5	6	7
1. HW	1.000						
2. SW	.664*	1.000					
3. PW	.715*	.703*	1.000				
4. MHC_t	.836*	.899*	.927*	1.000			
5. Resilience	.203*	.166*	.212*	.215*	1.000		
6. Depression	-.557*	-.477*	-.528*	-.573*	-.188*	1.000	
7. Anxiety	-.317*	-.277*	-.261*	-.311*	-.171*	.651*	1.000

373 **Note:** HW = hedonic well-being specific factor; SW= social well-being; PW = psychological well-
374 being specific factor; MHC_t= Mental health continuum total score; * = $p < 0.01$

375

376 **Table 5:** Correlation matrix for the retained specific subfactors and study outcomes, whilst
377 controlling for the correlation between the composite MHC-SF score and study outcomes.

Variables	1	2	3	4	5
1. HW	1.000				
2. SW	-.361**	1.000			
3. PW	-.289**	-.782**	1.000		
4. Resilience	0.044	-.065*	0.035	1.000	
5. Depression	-.172**	.104**	0.01	-.081**	1.000
6. Anxiety	-.109**	0.007	.078*	-.112**	.607**

378 **Note:** HW = hedonic well-being specific factor; SW= social well-being; PW = psychological well-
379 being specific factor; * = $p < 0.05$; ** = $p < 0.01$

380

381

382

Discussion

383
384

385 Competing psychometric models of the MHC-SF were assessed in the current study
386 comprising a large, demographically diverse, representative sample of athletes, that included
387 the novel specification of bi-factors models. While the default first-order three factor solution
388 showed marginally acceptable fit statistics, the best representation of the MHC-SF pertained
389 to a bi-factor model, comprising a strong general mental health factor, alongside relatively
390 weaker, but relevant, specific factors of Hedonic, Social and Psychological Well-Being. Such
391 findings are consistent with Keyes' (2002; 2005) early theorising of a multi-dimensional
392 mental health construct, with the added existence of an overarching mental health factor, as
393 supported in studies amongst general and clinical populations (De Bruin & Du Plessis 2015;
394 Hides et al., 2016; Jovanovic, 2015). Further, robust contributions of the general mental
395 health factor were evident in the nomological validity assessments, and when statistically
396 controlled for, relatively weak, but significant associations were revealed for the specific
397 factors.

398 In the present study we specified a unidimensional and higher-order two, and three-
399 factor solution as originally hypothesised by Keyes (2002). Athlete mental health studies tend
400 to apply unidimensional (Vella et al., 2020; McGivern, Shannon & Breslin, 2021) or three-
401 factor solutions (Salama-Younes, 2011; Foster & Chow, 2019), despite any converging,
402 population-specific, evidence for either model. The limited fit statistics for the unitary or
403 higher-order models presented in Table 1, particularly support several studies suggesting the
404 need for improvement in the factor structure of the MHC-SF (i.e., De Bruin and Du Plessis
405 2015; Hides et al. 2016; Jovanovic' 2015). Indeed, in one of the few MHC-SF factor analysis
406 studies amongst athletes (albeit items were modified for sport-specific mental health) Foster
407 & Chow (2019) outlined that an adequate fit for the three-factor solution would only be found

408 if residual errors were correlated. A further study amongst athletes (Salama-Younes, 2011)
409 removed five of the items to achieve adequate fit.

410 Correlating residual error terms is a controversial practice in factor analysis studies
411 (Gerbing & Anderson, 1984). Some authors (Reise, 2012) suggest that unless clear semantic
412 and/or theoretical overlap is evident, the correlation of error terms (both among and across
413 subfactors) equates to an unanalysed association and essential omission of a theoretically
414 meaningful variable(s). While Foster and Chow (2019) contended that all their correlated
415 error terms loaded onto the specific social well-being factor, correlating item error terms
416 within every specific MHC-SF factor (or across factors) would likely yield a much-improved
417 model fit due to model saturation (Hermida, 2015). However, given little semantic,
418 theoretical, or methodological grounds, we would advise against correlating error terms in
419 further research.

420 Additionally, in reviewing our findings we examined Salama-Younes' (2011)
421 decision to remove three items for the psychological well-being specific factor, and two items
422 from the social well-being factor, a practice often referred to as "scale purification". Wieland
423 et al. (2017) argued that scale purification should be made through a careful balance of
424 judgmental and statistical criteria. While statistical criterion has been discussed earlier,
425 judgmental criteria is based on a qualitative assessment of the appropriateness of survey
426 items to reflect theoretical interpretation (Carpenter et al., 2017). Upon inspection of item
427 wordings (see Table 3), we note that Salama-Younes' (2011) removed items reflective of
428 personality, sense of purpose and meaning, and one's contribution in society, all deemed
429 essential components of psychological well-being in philosophical traditions and
430 contemporary theories (Diener & Emmons, 1984; Ryan & Deci, 2000; Keyes, 2002; 2005).
431 As such, the removal of the aforesaid items in Salama-Younes' (2011) appeared to be based

432 largely on statistical criteria (i.e., improvement of fit statistics), and lacking a qualitative
433 justification.

434 We found that through testing a bi-factor model, that neither scale purification nor
435 correlating error terms are required. Specifically, we found excellent CFA fit statistics for the
436 retained model comprising a ‘general’ positive mental health factor, and three specific factors
437 of ‘Hedonic well-being’, ‘Social well-being’ and ‘Psychological well-being’. As such, our
438 findings amongst the athlete population support a number of factor analysis studies on the
439 MHC-SF (De Bruin and Du Plessis 2015; Hides et al. 2016; Jovanovic´ 2015), including a
440 recent multi-national study of 7,521 participants (Longo, Jovanović, Sampaio de Carvalho, &
441 Karaś, 2020). Notably, further bi-factor specific calculations showed most of the I-ECV item
442 values were $<.80$ rather than $>.80$ (see Table 3). Independent of the association between the
443 external variables and composite MHC-SF score, significant associations remained with
444 specific factors and external variables. Hence, we suggest a multi-dimensional structure
445 provides researchers and practitioners to isolate specific mental health components alongside
446 the unitary score.

447 However, we urge that specific factor scores should strictly be used to supplement the
448 unitary score, as most of the MHC-SF data converged on an overarching strong general
449 mental health factor. Specifically, and consistent with recent studies (Hides et al. 2016;
450 Longo, Jovanović, Sampaio de Carvalho, & Karaś, 2020), relative to the specific factors, the
451 general factor exhibited high reliability, and explained the majority of model and item
452 variance. Moreover, the correlations between specific factors and external variables were
453 weak when the unitary score was statistically controlled for. Such findings support structural
454 equation modelling data (Hides et al. 2016) that the predictive validity of bi-factor version of
455 MHC-SF’s is attributable to its general factor.

456 Lastly, to explain the somewhat contradictory finding that the higher-order
457 unidimensional model exhibited poor model fit, whereas the bi-factor model's strength was
458 attributable to the general, overarching positive mental health construct, Reise, Cook and
459 Moore (2015) have suggested that global constructs such as mental health, intelligence and
460 personality will inevitably exhibit multidimensionality. Hence, positive mental health can be
461 considered a single construct pertaining to a global evaluation about one's subjective well-
462 being, existing alongside multiple concepts, such as emotional, psychological, and social
463 well-being (Longo, Jovanović, Sampaio de Carvalho, & Karaś, 2020).

464 *Practical and methodological recommendations*

465 Some practical recommendations from the study include the use of Keyes' (2002) two
466 continua model of mental health when considering the design and evaluation of mental health
467 literacy and awareness programmes. The two continua model provides a narrative around
468 mental health that is less stigmatising, and less medicalised than what has previously been
469 used (Hughes and Leavey, 2012). For example, Uphill, Sly & Swain (2016) outline that the
470 use of the two continua model to mental health can offer athletes a narrative regarding how a
471 successful, high functioning, athlete can simultaneously experience well-being and have a
472 mental illness. Such examples are evident in recent studies among adolescent athletes (see
473 Wynters et al., 2021). Moreover, willing athletes who self-characterise themselves as being
474 well, yet experiencing or currently working through a mental illness could act as role models
475 to help destigmatise mental illness. Additionally, the specific factors found within the MHC-
476 SF in the present study could help practitioners explore the importance of social relationships,
477 psychological meaning and purpose, and emotional health to one's overall mental health
478 (Giles et al., 2020).

479 In a research capacity, the MHC-SF could be integrated into monitoring and
480 evaluation of programme effectiveness, wherein the general score is calculated and
481 supplemented by specific factors to determine any self-reported change. The MHC-SF is
482 relatively quick to complete, easy to understand, and the proposed calculations are primary
483 functions within statistical software packages such as SPSS (Longo et al., 2020). When
484 examining more complex structural equation modelling, further epidemiological, cross-
485 sectional studies could model the bi-factor version of the MHC-SF using the figure
486 schematics presented in this study and specify predictions with relevant mental health
487 variables (e.g., psychological needs satisfaction, drug misuse, trauma history). Doing so will
488 help advance knowledge of athlete mental health such that athlete experiences and self-
489 reports are grounded in Keyes' (2002) theory, helping ensure precision and an accurate
490 representation of the correlates of interest (Giles et al., 2020). With the advances in sport
491 psychiatry, the MHC-SF could also be used alongside ill-being measures in a more holistic
492 assessment of athletes who present with psychological issues (Mistry, McCabe & Currie,
493 2020).

494 *Limitations*

495 There were several limitations, namely, the cross-sectional design meant that test-retest
496 reliability remains unassessed. The mean age was 32, and any extrapolation to younger age
497 groups involved in competitive sport is restricted. Although individual and coactive sports
498 were represented in the sample, the types of sports was limited to equestrian, rugby, Gaelic-
499 games and running, and the inclusion of more sports would have been more representative.
500 The vast majority (86.4%) of participants classified themselves as non-or sub-elite (e.g.,
501 amateur, local leagues), and the 13.6% of participants who self-classified as elite is
502 comparatively higher than the National Collegiate Athletics Association's (2019) estimate of
503 6%. While definitions of elite athlete level vary according to the sport, standard of

504 participation, and global context (Swann et al., 2015), psychological pressure to succeed is
505 higher at the elite level. Given a recommended participant-to-parameter ratio of at least 10:1
506 in structural equation modelling (Jackson, 2003) a larger sample of athletes could have
507 warranted a splitting of the sample into subgroups (see Longo, Jovanović, Sampaio de
508 Carvalho, & Karaš, 2020, for a multinational analysis), to determine if the bi-factor model of
509 the MHC-SF holds true in the various competitive athlete levels and demographic factors. To
510 this end, future research should aim to achieve a representative demographic sample when
511 evaluating mental health measures, screening tools, and diagnostic practices. The present
512 sample was mainly female, which may reflect a higher likelihood of females to complete
513 mental health surveys or engage in the topic of mental health. Further, important data on
514 race/ethnicity, socio-economic status and education/employment were absent. Finally, mental
515 health literacy levels (i.e., knowledge of mental health, mental illness and self-management)
516 differs across countries (McGivern et al., 2021), this may explain athlete participation rates
517 and openness to engage in the survey.

518 **Conclusion**

519 Overall, the bi-factor version of MHC-SF represents a theoretically grounded and valid
520 measure of positive mental health in athletes. Sport organisations, researchers and
521 practitioners may consider integration of the MHC-SF into monitoring and evaluation of
522 programme effectiveness, and/or screening of positive mental health. We propose that future
523 use of the MHC-SF should entail the calculation of a composite score in the knowledge that it
524 is explaining the vast majority of MHC-SF model and item variance. However, given some
525 contribution of the specific factors, supplementary analysis may involve the calculation of
526 specific factors - albeit strictly to supplement the composite score. Keyes' (2002) two
527 continua model and the specific factors found within the associated MHC-SF in the present
528 study could serve as discussion points in future athlete mental health interventions, and

529 continue to ground athletes' experiences in theory in future research studies. Limitations of
530 this cross-sectional study relate to the higher distribution of female-to-male participants,
531 higher age category of athletes, and the test-retest reliability of the MHC-SF remains
532 unassessed in athlete populations. Finally, conducting further longitudinal factor analysis
533 studies with a broader range of sports can provide a more comprehensive psychometric
534 instrument for athletes.

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