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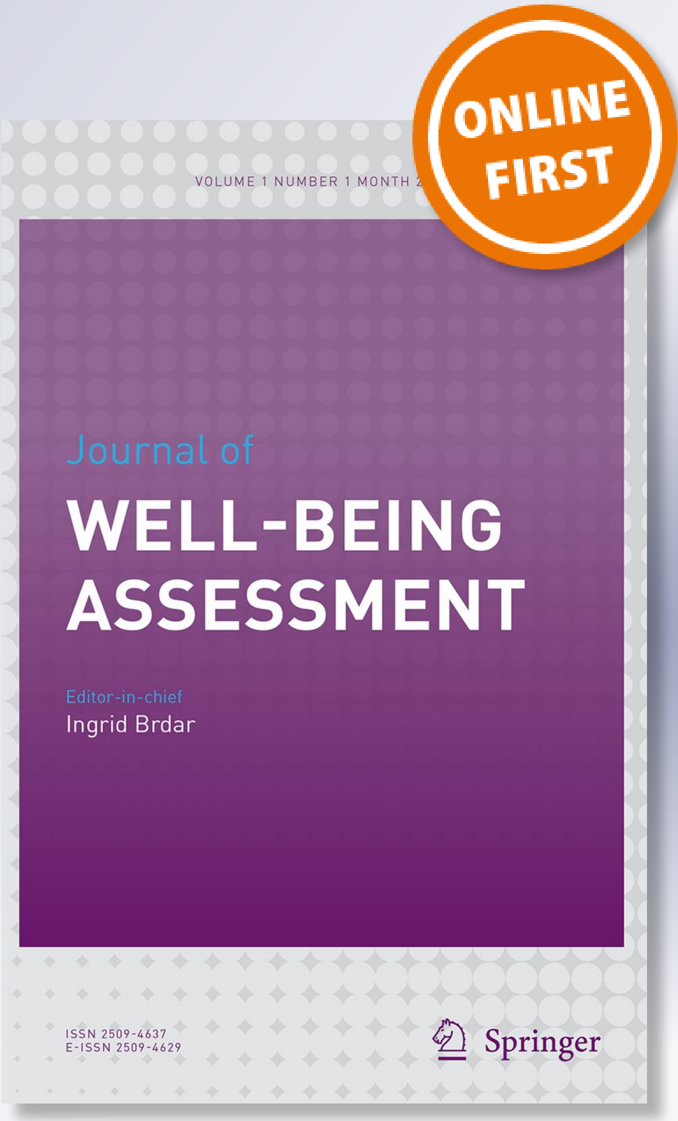

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ORIGINAL RESEARCH

Study of the Mental Health Continuum Short Form (MHC-SF) amongst French Workers: a Combined Variable- and Person-Centered Approach

Franck Jaotombo [1] Published online: 31 August 2019

Abstract
Keyes's theory-driven model of mental health uses a diagnosis which leads to three levels of positive feelings and positive functioning: *languishing, moderately mentally healthy and flourishing* (Keyes 2002). Although these three-level categories may be justified for a unidimensional factor structure, or a factorial structure using summated scales, the recent works supporting a multidimensional structure of the Mental Health Continuum Short Form (MHC-SF) suggest the adoption of shape-based rather than level-based categories of mental health (Morin et al. 2017). This research aims at testing the empirical validity of Keyes's taxonomy and its relationship to psychosocial functioning. We first adopted a variable approach by selecting the optimal factor structure for the MHC-SF: the bifactor exploratory structural equation modeling (Bi-ESEM). Following with a person-centered approach, we used a latent profile analysis on the factor scores of the Bi-ESEM. Psychosocial risks indicators were used as outcomes for testing the criterion validity of the models on a sample of 1065 French workers. Results show that the mental health subgroups are more intricate than the three-levels categories originally theorized by Keyes (2002, 2005). While the general Bi-ESEM factor warrants three levels akin to those of Keyes, accounting for the specific factors reveals two profiles of languishing: the *hedonic languishers* characterized by a low level of emotional wellbeing, and the *eudaimonic languishers* characterized by a low level of psychological wellbeing. Both variable and person-centered approach confirm Keyes's initial statements (Keyes 2007) that those who are languishing exhibit the highest levels of psychosocial risks while those flourishing display the lowest. A rule-based diagnosis derived from a decision tree method is suggested as an alternative to a level-based taxonomy.

Keywords Mental health continuum · Flourishing · Bifactor ESEM · Latent class analysis · Factor mixture analysis · Psychosocial risks · Classification and regression trees

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Research that started in the early 2000s has seen the short form of the Mental Health Continuum (MHC-SF) validated in several continents and cultures, such as Chinese, Vietnamese, African, Dutch, Serbian, Polish and Italian, as an instrument for measuring mental health (Guo et al. 2015; Joshanloo and Jovanović 2016; Joshanloo and Lamers 2016; Petrillo et al. 2015; Rogoza et al. 2018). Research carried out in the last previous decade has consistently shown that the MHC-SF has a three factor structure, but the development (or rediscovery) of methods such as bifactor modeling (Reise, 2012) and exploratory structural equation modeling (Asparouhov & Muthén, 2009) has led to renewed debates about its structure. The main questions regarding the factor structure of the MHC-SF could be summarized by paraphrasing Morin et al. (Morin et al. 2017) as following: (a) Do the three factors of MHC-SF retain meaningful specificity over and above the overarching construct of mental health? Or, (b) does mental health exist as a global entity including specificities such as the three MHC-SF factors? Or, (c) Do the three correlated factors of the MHC-SF represent dimensions without a common core?

The latest studies suggest that the three-factor independent cluster confirmatory factor analysis model is no longer tenable, and that among the other possibilities, the bifactor exploratory structural equation modeling models have consistently shown the best fit (Longo et al. 2017; Rogoza et al. 2018; Schutte and Wissing 2017; Silverman et al. 2018).

Additionally, some earlier findings (Keyes, 2007) demonstrated that flourishing was associated with positive outcomes for individuals and society in that Flourishing adults missed the fewest workdays, had the fewest health problems, made the least use of healthcare services and exhibited the highest levels of psychosocial functioning.

However, to date, none of these facts have been confirmed in France, nor in an occupational context.

Furthermore, whilst a DSM[1]-inspired diagnosis of mental health has been clearly advocated by Keyes (2005) and shown to be sound by several studies (Bornstein et al. 2012; Kendler et al. 2011; Keyes et al. 2017; Keyes and Simoes, 2012), there is hardly any inductive empirical research that supports Keyes's three-category mental health taxonomy: *flourishing*; *moderately mentally healthy*; *languishing*. Given an appropriate operational definition of mental health and a sufficiently varied sample of respondents, it should be possible, using statistical methods, to identify - at least to some extent - subgroups of respondents embodying the profiles predicted by Keyes's theoretical work.

Hence, this research aims at testing the empirical validity of Keyes's taxonomy and its relationship to psychosocial functioning. We used data from a sample of 1065 French workers to: 1) validate the factor structure of the MHC-SF; 2) use the resulting factor structure to explore subgroups of mental health through latent profile analysis; 3) test the predictive power of the retained model on psychosocial risks indicators, both through a variable- and a person - centered approach.

This paper starts with a brief review of literature on mental health measured by the MHC-SF, followed by the different methods used for factor analysis and classification analysis. Then the results are presented and discussed. The paper concludes by setting out the limitations of the research and offering suggestions for future work.

[1] Diagnostic and Statistical Manual of Mental Disorders

1 Flourishing and Mental Health

Traditionally mental health has been investigated according to an illness model, that is, most research has been concerned with mental ill health and its consequences. Lately, however, there has been a shift in perspective, as the World Health Organization (WHO) now defines mental health as "a state of wellbeing in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community"[2] (Herrman et al. 2004). Wellbeing has been the subject of serious studies in recent decades (Diener et al. 1999; Ryan and Deci 2001), particularly since the advent of positive psychology and positive organizational scholarship (Cameron and Spreitzer 2011; Donaldson and Ko 2010). There is ongoing debate about the concept of subjective wellbeing. The hedonic school considers wellbeing mainly in terms of positive experiences and feelings (Diener et al. 1999; Kahneman et al. 2003), but some researchers take a more eudaimonic perspective on wellbeing (Ryan and Deci 2001; Ryff 1989; Ryff and Singer 2006), viewing it in terms of the extent to which one is able to develop one's potential, self-actualization and optimal functioning. A few authors have sought to integrate these schools of thought and suggested that positive experiences and positive functioning are aspects of a single, unitary construct (Keyes 2002; Keyes et al. 2002). In a seminal paper Keyes (2002) defined mental health as flourishing, suggesting that - like mental ill health - mental health could be operationalized as a syndrome of symptoms of an individual's mental wellbeing. Keyes also emphasized that there is more to wellbeing than feeling good or functioning well, arguing that social environment also has a significant impact on wellbeing (Keyes 2002; Keyes 1998) and hence operationalized a multidimensional wellbeing measurement model based on three constructs: emotional wellbeing, social wellbeing and psychological wellbeing. Emotional wellbeing is generally measured as life satisfaction, the presence of positive affect and the absence of negative affect. Social wellbeing is defined and measured in terms of Keyes's five dimensions of social wellbeing (Keyes 1998), namely social integration, social contribution, social coherence, social actualization and social acceptance. Psychological wellbeing is measured in terms of Ryff's six dimensions of psychological wellbeing (Ryff 1989), namely self-acceptance, personal growth, purpose in life, positive relations with others, autonomy and environmental mastery. The MHC-SF was designed to measure mental health thus defined. Keyes (2002, 2005) suggested that since conceptually and empirically, mental wellbeing indicators fall into clusters that mirror those of the major depressive episodes in the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association 2000), the latter could provide a theoretical framework for the 'diagnosis' of mental health. Thus, individuals are diagnosed as *flourishing* if they score highly on at least one measure of hedonic wellbeing and on at least half of the items on positive functioning (social wellbeing & psychological wellbeing). Individuals with a low score on at least one measure of hedonic wellbeing and low scores on more than half of the items on positive functioning (social wellbeing and psychological wellbeing) are diagnosed as *languishing*. Those who are neither flourishing nor languishing are deemed *moderately mentally healthy*. This said, (Keyes et al., 2008, 2005, 2007) has recommended the use of both categorical and continuous assessments of mental health.

Some earlier findings (Keyes 2007) demonstrated that flourishing was associated with positive outcomes for individuals and society in that adults who were diagnosed as completely

[2] http://www.who.int/mediacentre/factsheets/fs220/en/ (retrieved October 05, 2018)

mentally healthy missed fewest workdays, had the fewest health problems, made least use of healthcare services and exhibited the highest levels of psychosocial functioning. Several of these observations have been confirmed more recently (Keyes and Simoes 2012). In addition, the MHC-SF has led to insights into the risk of future mental illness: gains in mental health were shown to predict declines in mental illness and decline in mental health to predict increases in mental illness (Keyes et al. 2010). In short, complete mental health is not only the absence of illness but also the presence of mental health (Keyes et al. 2010).

2 Factor Structure of the MHC-SF

Previous research suggested that the MHF-SF has a three-factor structure, and some provided support for a second-order hierarchical factor model (Gallagher et al. 2009; Petrillo et al. 2015), but recent methodological developments have called these findings into question. Most of the earlier research was based on traditional independent cluster model confirmatory factor analysis, whereby items are allowed to load on one, and only one factor, such that no other source of variance is permitted. Several authors have argued that this assumption is not tenable and that at least two other sources of variance should be considered before any conclusion is drawn. One school of thought considers that cross loadings, i.e. the loading of items on non-target factors, are the main excluded sources of variance (Asparouhov et al. 2015; Joshanloo and Jovanović 2016; Marsh et al. 2014, 2009): they rely on exploratory structural equation modeling confirmatory factor analysis as a remedy. Another school of thought is that the main source of extra variance in models should be represented as an overarching general factor (Chen et al. 2012, 2006; De Bruin and Du Plessis 2015) and recommends the use of bifactor confirmatory factor analysis models. A recent study by Morin et al. (2017) integrated these two approaches, giving good reasons for taking into account both sources of variance and arguing that parameter estimates might be biased if either were neglected (Morin et al. 2016). Morin et al. (2017) suggested that bifactor orthogonal exploratory structural equation modeling (Bi-ESEM) should also be considered, although the final decision should be based on theoretical considerations.

The latest studies have convincingly led researchers to believe that the three factor independent cluster model CFA model is no longer tenable and that among the other possibilities such as the three-factor exploratory structural equation modeling and bifactor models, the bifactor exploratory structural equation modeling models have consistently shown the best fit (Longo et al. 2017; Rogoza et al. 2018; Schutte and Wissing 2017; Silverman et al. 2018). The bifactor structure of the MHC-SF has been replicated over different types of samples in many nations, the latest confirmation being a 38-nation study for cross-cultural studies (Żemojtel-Piotrowska et al. 2018). However, to date, we are not aware of any such study in France and even less so in an occupational context.

3 Psychosocial Risk Indicators

Psychosocial risk is often used as a generic term for undesirable work outcomes related to stress and ill health at work (Cousins et al. 2004; Leka et al. 2008, 2010; MacKay et al. 2004). In order to examine the predictive capacity of the MHC-SF with respect to mental health we consider three types of psychosocial risks in the workplace: absenteeism, presenteeism and turnover intention. Absenteeism has been defined as “the failure to report to work schedule” (Johns 2008, p. 160) and is widely recognized as a significant source of financial and productivity losses for all types of organizations (Asfaw et al. 2014). Although there are several ways of operationalizing absenteeism, we consider only two very broad definitions: total days of work missed, and days missed due to management practices in the workplace.

As business leaders and organizational managers strive to reduce absenteeism one might be misled into thinking that a high level of work attendance is always desirable, but it can reflect presenteeism, being sick yet at work (Aronsson et al. 2000). Presenteeism is often a consequence of stress or is facilitated by stressors such as the loss of control (Aronsson and Gustafsson 2005). Presenteeism is negatively related to wellbeing (Baeriswyl et al. 2017; Brown, Gilson, Burton & Brown et al. 2012), for example as an antecedent of emotional exhaustion and hence burnout. Some studies suggest that presenteeism is as pervasive as absenteeism (Hansen and Andersen 2008) as a result of personal factors such as an over commitment to work or work-related factors such as time pressure and relationships with colleagues.

As for turnover intention, turnover is negatively associated with satisfaction at work, which is one indicator of wellbeing, and turnover intention is one of the strongest predictors of turnover (Tett and Meyer 2006), so it is natural to assume that wellbeing is a negative predictor of turnover intention (Brunetto et al. 2012; Siu et al. 2014). Stress and many of the known stressors are well-known predictors of turnover intention (Elangovan 2001; Kim and Stoner 2008), yet positive resources such as psychological capital can also be used to counteract stress and reduce turnover intention (Avey et al. 2009). Therefore, we were naturally drawn to study the role of mental health in reducing turnover intention.

At this point we may summarize the facts as following: there is hardly any inductive empirical research supporting Keyes’s three-category mental health taxonomy, and the multidimensional bifactor structure of the MHC-SF has never been tested in French, nor its connection to psychosocial functioning in an occupational context. Based on a sample of 1065 French workers, we proceed to validate the factor structure of the MHC-SF and use the resulting factor scores to explore subgroups of mental health through latent profile analysis. Then we test the predictive power of the retained model on psychosocial risks indicators, both through a variable- and a person-centered approach.

4 Methods

4.1 Sample

Data were collected from a random sample of French respondents who had been professionally active over the last year by a local French polling company, via an online survey. The final sample comprised 1065 observations (43.1% male; 56.9% female) and had a mean age of 37.74 years (range: 18–60, $SD = 10.07$). The median yearly income was in the 12,000 € - 25,000 € range. The most frequent educational level was 2 to 3 years of post-high school education and only 27% of the participants were single. All the main regions of France and occupational sectors were fairly represented. In short, this was a fairly diverse sample of French participants of average socioeconomic status.

4.2 Measures

Mental health was measured using the 14-item MHC-SF. Responses were given using a six-point scale ranging from 1 (never) to 6 (every day).[3] Examples of items are: "During the past month, how often did you feel" [stem] "happy?" (emotional wellbeing), "that you had something important to contribute to society?" (social wellbeing), "good at managing the responsibilities of your daily life?" (psychological wellbeing).

In our exploration of the criterion validity of the measurement model we used six items as manifest indicators of psychosocial risks. Several of these have been discretized to yield sufficient variability and avoid extreme skewness and kurtosis. Absenteeism was measured using two items: general absenteeism (*GenAbs* - "Roughly, how many work days have you missed over the last year?") and management absenteeism (*ManAbs* - "Over the last year, how many work days have you missed due to management practices?"). Presenteeism was measured with two items: physical presenteeism (*PhysPres* - "Over the last six months, how often monthly did you go to work despite feeling physically unable to?) and psychological presenteeism (*PsycPres* - "Over the last six months, how often monthly did you go to work despite your feeling psychologically unable to?)

Turnover intention was measured using two items, *Turnover* ("Over the last year how often have you thought of changing your job? And *Unhappy* ("Over the last year how often have you thought that you felt really unhappy at work?"), responses were given using a five-point Likert scale ranging from "never" to "always."

4.3 Factor Structure Analyses

We adopted a bifactor orthogonal exploratory structural equation modeling with a zero-target rotation. All 14 items load on a single general factor and on all three domain-specific factors such that the loading on the non-primary factors is constrained to be close to zero. All pairwise correlations between the factors are set to zero. It is implied here that there is an underlying overall general factor (G-factor) as a main source of variance for all the MHC-SF item indicators, and three specific factors (S-factors) - emotional wellbeing, social wellbeing & psychological wellbeing - explaining variance unexplained by the former; the remaining unexplained variance is represented by the item residuals. As such, the overall *level* of mental health is captured by the G-factor while the S-factors' scores encapsulate the scores of emotional, social and psychological wellbeing, controlling for the G-factor.

For the psychosocial risks' indicators, we specified a three factor independent cluster model CFA structure where the 6 indicators load by pairs on a corresponding absenteeism, presenteeism and turnover factors.

MLR estimation was used given that the items can be considered quasi-continuous and quasi-normal, but with a few missing data (Wang and Wang 2012). All estimations were carried out using Mplus 7.0 software (Muthén and Muthén 2012) and IBM SPSS statistics (SPSS Inc. 2012).

[3] The full scale is available and permission for use is also granted by Keyes (2009) at: https://www.aacu.org/sites/default/files/MHC-SFEnglish.pdf [Online, retrieved October 5, 2018]

4.4 Construct Validity

Convergent Validity Convergent validity represents the extent to which several operationalizations of the same construct converge, in other words, the extent to which "multiple methods of measuring a variable provide the same results" (O'Leary-Kelly 1998, p. 399). We used an extended version of Fornell and Larcker's criteria (Fornell and Larcker 1981a, b; O'Leary-Kelly 1998) requiring the following: 1) Quasi-unidimensionality. Fornell and Larcker's original criterion specified strict unidimensionality (no cross loadings) but this may bias parameter estimates in the case of multi-dimensional constructs (Marsh et al. 2014, 2009; Morin et al. 2016) and so we aimed to reduce non-target factor loading to be close to zero (preferably $< .100$ in standardized units); 2) Standardized average variance extracted (AVE) greater than .5, meaning that each factor should explain more variance than the unknown sources of variance (residuals); 3) Items with residual standardized values above .5 (or r-squared below .5) should be scrutinized as this may indicate problems.

Discriminant Validity Discriminant validity is concerned with the extent to which a construct is operationalized differently from theoretically distinct constructs. Two concepts that have discriminant validity with respect to each other should, according to Fornell and Larcker's criteria (Fornell and Larcker 1981a, b; Voorhees et al. 2016), exhibit the following characteristics: the standardized average variance extracted for each factor measuring each concept (e.g. emotional wellbeing and psychological wellbeing) should be greater than the variance shared by those factors (i.e. their squared correlations), and cross loadings should be minimized as high cross loadings indicate that an item does not discriminate well between the factors involved. These requirements are easily fulfilled by the bifactor models since all inter-factor correlations equal zero and the cross loadings between the domain-specific factors are close to or equal to zero.

4.5 Criterion Validity

Criterion validity is the extent to which the operationalized construct actually predicts something it should theoretically predict as well as its ability to distinguish groups it should theoretically separate (Cronbach and Meehl 1955; Trochim et al. 2015).

Variable Approach The theory states that mental health should be negatively associated with psychosocial risks. Structural equations modeling of the MHC-SF should yield latent variables that are negative predictors of the (latent) variables representing psychosocial risks; in other words, when mental health increases, psychosocial risks should decrease. Although structural equations modeling can be used to ascertain causality if the design is appropriate, the predictions do not have to be causal - even the predictive ability of cross-sectional models can be evaluated. In the following, the factors of each of the bifactor exploratory structural equation modeling are specified to predict the factors of psychosocial risks, in a typical latent variable structural equation modeling.

Person-Centered Approach Previous research has shown that Keyes's diagnostic framework identifies individuals who have a high level of psychosocial functioning as flourishing and distinguishes them from individuals who display poor psychosocial functioning and are identified as languishing. We used latent class analysis based on the bifactor exploratory structural equation modeling factor scores to identify subgroups of mental health profiles, which we predicted would be consistent with Keyes's observations i.e. the healthiest among the subgroups would display the lowest overall levels of psychosocial risks, and the worst functioning subgroups will demonstrate the highest overall levels of psychosocial risks. Latent class analysis is akin to applying exploratory factor analysis to individuals (statistical unit) rather than to variables: it is a form of model-based, unsupervised 'clustering.' When the variables involved are continuous, latent class analysis is referred to as latent profile analysis (McLachlan and Peel 2000). The optimal number of classes is reached when most of the following conditions are met: 1) The log-likelihood value is maximal (as close to zero as possible); 2) The information criterion indices (Akaike = AIC; Schwartz = BIC; sample size adjusted BIC = ABIC) are minimal; 3) The likelihood ratio tests (LRTs) (McLachlan 1987; McLachlan and Peel 2005) comparing a model with k classes and a model with $k + 1$ classes yield p values greater than .05, meaning that the Vuong-Lo-Mendell-Rubin Test for model equality is not rejected (Lo et al. 2001; Vuong 1989); 4) The relative entropy is greater than .60 and close to 1; 5) The final classes shape and size are theoretically sound and lead to a meaningful interpretation. Here the G-factor scores define the overall level of mental health whereas the S-factors' scores are more informative on the shape of the mental health profiles and their difference. Once the optimal number of classes ascertained, each observation is assigned to its most probable class and the resulting mental health class variable is used to predict the outcome variables (the psychosocial risks factor scores) in a typical one-factor analysis of variance, where we compare the psychosocial risks levels of the mental health profiles.

The earlier approach of latent class modeling does not account for the covariates (psychosocial risks indicators) and is therefore deemed a *free* latent class analysis. However, including the covariates is more realistic and highlights the specificity of each profile with regard to the psychosocial risks' indicators. For this, we use a latent class regression model - also called *conditional* latent class analysis - where the outcome variables are specified to predict the latent mental health class membership (Wang and Wang 2012; Wetzel et al. 2016).

4.6 Reliability

"Reliability pertains to the consistency or stability of a measure and is inversely related to the degree to which a measure is contaminated by random error" (O'Leary-Kelly 1998, p. 394). Cronbach's alpha is the most widely used indicator of reliability, but it is not used here as it has been widely criticized and is not really appropriate for bifactor models (Morin et al. in Press; Sijtsma 2009). McDonald's omega (ω) (McDonald 1970) is gaining a wider recognition as a measure of the reliability of CFA models and others. Recently, several omega indices have been proposed as indices of the reliability for bifactor models such as the omega hierarchical (ωh) and the explained common variance (Morin et al. 2017; Rodriguez et al. 2016). We will remind here only the generic formula for omega (equation 1), where the λ_i are the factor loadings and δ_i the factor residuals (uniqueness):

$$\omega = \frac{\left(\sum|\lambda_i|\right)^2}{\left(\sum|\lambda_i|\right)^2 + \sum\delta_i} \tag{1}$$

4.7 Diagnosis for Clinical or Managerial Purposes Based on Decision Trees

The person-centered approach usually assigns each observation to a class of mental health. From a clinical perspective a simple decision rule based on the original item responses values is very useful, even necessary. One simple way of implementing this is through classification trees (Breiman et al. 1984). Given a categorical outcome (the mental health classes variable) and a set of predictors (the 14 MHC-SF items), the classification tree model will divide the set of possible values of the predictors into several distinct and non-overlapping regions. For every observation that falls into one region we make the prediction that the outcome class will be the most commonly occurring class. The choice of the regions is done such that each step minimizes a function measuring the classification error rate like the *Gini* or the *Entropy* index. This process is repeated in each region, looking for the best predictor and the best cut point, according to a process called recursive binary splitting (for details, see James et al. 2013), and until the minimum number of observations per region is reached (here, 20 per default). These successive predictor splitting leads to a set of rules that may be represented by a decision tree. The accuracy of the rule can then be tested by making – for instance – one hundred predictions and by averaging the hit rate (*accuracy*) over all these predictions. Here, a decision tree is implemented with R software (R Core Team 2018) on the *caret* (Kuhn 2018) and *rpart* (Therneau & Atkinson, 2018) packages.

5 Results

5.1 Factor Structure Analyses

Both the bifactor exploratory structural equation modeling and the three-factor psychosocial risks models demonstrate an excellent fit (Table 1). Although the cross loadings in the Bi-ESEM are not large (Table 2), discriminant validity is a concern in the cases of item #14 (*purpose in life* loads similarly on the emotional wellbeing and psychological wellbeing factors) and item #12 (*personal growth* loads more strongly on a non-target factor, emotional wellbeing, than on psychological wellbeing). This said, applying Fornell and Larcker's criteria to the factors removes all questions about discriminant validity as there is no shared variance between the Bi-ESEM factors, and the model has high average variance extracted. Additionally, although items #12 and #14 load weakly on their target specific factors, they do load very strongly on the general factor, which suggests that they function more as indicators of the general overarching factor rather than the specific factors. Indeed, even when accounting for cross loadings, most of the indicators load more strongly on the general factor than they do on the specific factors. The relevance of an overarching G-factor is thus reinforced.

5.2 Construct Validity

Variable Approach The two measurement models (Bi-ESEM and three-factors psychosocial risks) display each a very good construct validity as shown in Tables 2 & 3. The variance extracted by each factor is well above the minimum required standard value of .5. The omega values are also all above .7, and even above .8 for the MHC-SF construct. We therefore assume with confidence that there is more explained variance in our models than in other unknown sources of variance. When we examine the value of all the reliability indices, including

Table 1 Fit of (competing) models compared to the orthogonal bifactor exploratory structural equation modeling

Model	Adj χ^2	df	p value	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR	AIC	BIC	A-BIC
3F-CFA	564.57	74	<.001	.079	[.073–.085]	.921	.903	.064	40,812.81	41,036.49	40,893.57
3F ESEM	220.65	52	<.001	.055	[.048–.063]	.973	.952	.021	40,403.08	40,736.12	40,523.32
Bi-CFA	285.19	63	<.001	.058	[.051–.064]	.964	.948	.030	40,445.00	40,723.36	40,545.50
Bi-ESEM	137.50	41	<.001	.047	[.038–.056]	.984	.966	.015	40,302.18	40,689.90	40,442.15
3F-PSR	10.90	6	.09	.028	[.000–.053]	.997	.993	.012	23,539.82	23,644.22	23,577.52
Good Fit				≤ .06	[.000–.080]	≥ .95	≥ .95	≤ .080	Minimum	Minimum	Minimum

Fit indices:Adj χ^2 : Adjusted chi-square; RMSEA: Root Mean Square Error of Approximation; CI: Confidence interval

CFI Comparative Fit Index; *TLI* Tucker-Lewis Index; *SRMR* Standardized Root Mean Square Residual; *AIC* Akaike Information Criterion

BIC: Bayesian Information Criterion; A-BIC: Adjusted BIC. **Measurement models:** Mental Health: 3F-CFA: three-factor confirmatory factor analysis; 3F-ESEM: three-factor exploratory structural equation modeling; Bi-CFA: orthogonal bifactor confirmatory factor analysis; Bi-ESEM: orthogonal bifactor exploratory structural equation modeling. Psychosocial risks: 3F-PSR: three-factor confirmatory factor analysis

Table 2 Factor structure and validity indices of the orthogonal bifactor structural equation modeling

Items	Factor Loadings General MHC	Emotional wellbeing	Social wellbeing	Psychological wellbeing
MHCA1	.73***	.53***	*−.01*	*.01*
MHCA2	.79***	.42***	*.00*	*.00*
MHCA3	.72***	.53***	.09***	.06*
MHCA4	.64***	*−.02*	.28***	*−.02*
MHCA5	.34***	*−.03*	.27***	−.11**
MHCA6	.45***	*.02*	.74***	*−.03*
MHCA7	.45***	.05*	.66***	*.04*
MHCA8	.48***	*.01*	.65***	*.00*
MHCA9	.65***	*.05*	.06**	.40***
MHCA10	.53***	*.10****	*−.01*	.69***
MHCA11	.70***	*−.03*	*.02*	.33***
MHCA12	.79***	*−.17****	*.01*	*.13*
MHCA13	.63***	−.15**	−.13***	.39***
MHCA14	.80***	.19***	−.04*	.20***
Omega	.95	.93	.83	.91
AVE	.65	.81	.54	.66

**p < .05; **p < .01; ***p < .00;* AVE: Average Variance Extracted

hierarchical omega (ωh) and explained common variance (ECV) for the Bi-ESEM model (Supplement 2) we notice that the G-factor has predominance over the S-factors, and among the latter, social wellbeing has more influence than the two others.

Person Centered Approach In this section factor scores derived from the Bi-ESEM are used as variables for latent profile analysis (an instance of *free* latent class analysis). First, we tested models with 2 to 6 latent classes allowing for free estimation of the variances (Supplement 5). The best fitting model yields three levels-like classes quite different from Keyes's original theory, not only based on their shapes but also on their class proportion (4.6% in the upper level, 51.1% in the middle level and 44% in the lower level when the original Keyes's diagnostic should yield respectively 39.1%, 53.5% and 7.4% in our sample). Furthermore, levels-based profiles are redundant with the variable approach and does not bring any new

Table 3 Psychosocial risks factor structure and validity indices

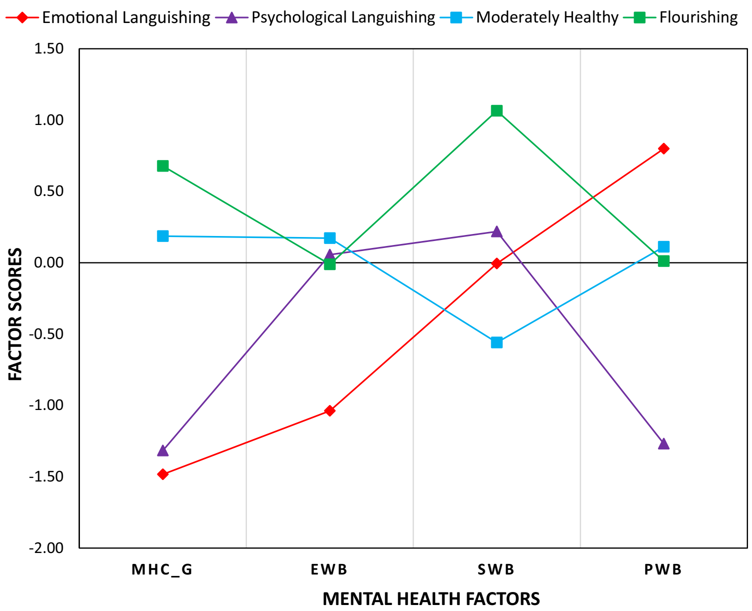
	Items	Factor loadings Absenteeism	Presenteeism	Turnover Intention
Factor Structure	General absence rate	.56***	–	–
	Management absence rate	.90***	–	–
	Physical presenteeism	–	.77***	–
	Psychological presenteeism	–	.95***	–
	Thoughts of leaving	–	–	.84***
	Perceived unhappiness	–	–	.92***
Correlations	Presenteeism	.40***	–	
	Turnover Intention	.27***	.54***	–
Validity indices	Omega	.71	.85	.88
	AVE	.57	.75	.78

**p < .05; **p < .01; ***p < .001;* AVE: Average Variance Extracted complementary information to our model. Additionally, an attempt to extract four classes with freely estimated variances yields a spurious class containing only 1% individuals while not solving the previous contradictions. Therefore, we resumed our analysis by constraining an equality of variance across the latent groups. Several models have been tested and replicated, from 2 to 7 classes (Table 6). While the information criteria keep diminishing and entropy increasing, the LRT tests remain stable as we reach 5 classes. This highly suggests that there is no significant difference between the 4-classes model and the models specified with more classes. Moreover, the interpretability of the profiles obtained beyond five classes is problematic. Hence, we retain the optimal solution with four most meaningful classes (Fig. 1). The majority of the sample (54%) was assigned to a class which has approximately average-level scores for all factors. This class undoubtedly represents the *moderately mentally healthy* and could be considered as the reference class. Then we have two classes with low scores on the G-factor. Since the G-factor score captures the overall levels of mental health, these two classes are deemed languishing: one has low emotional wellbeing and can be described as the *hedonic / emotional languishing* category, whilst the other has low psychological wellbeing and can be described as the *eudaimonic / psychological languishing* category. The last class demonstrates high general mental health and high social wellbeing and has no low scores on any of the factors and can therefore be considered as the *flourishing* category. As elucidated in Supplement 4, there are significant differences between these four classes. However, the factor which discriminates them best is the social wellbeing. The general factor does not discriminate between the two languishing categories, the emotional wellbeing factor does not discern either flourishing nor moderately mentally healthy from psychological languishing, and the psychological wellbeing factor does not distinguish flourishing from moderately mentally healthy.

5.3 Criterion Validity

Variable Approach As shown in Tables 4 & 5, latent regressions of the Bi-ESEM factors on the psychosocial risks' factors confirm the negative associations between mental health and psychosocial risks. The general factor predicts a decrease of each of the three psychosocial risks factors, however, only social wellbeing predicts a small but significant decrease in absenteeism, and only psychological wellbeing does not predict a significant decrease in presenteeism, while all the factors predict a significant decrease in turnover intentions. This result clearly suggests that there could be additional specific relevant effects that the general factor does not account for (Table 6).

Person Centered Approach Here, we save the factor scores of the psychosocial risks measurement model and we compare them across these four newly obtained mental health classes. In short, we conduct one-factor analyses of variances over these four groups, then we carry on with pairwise comparisons and apply a Bonferroni correction for p values. Results show that there is a significant overall effect of the mental health classes variable on each of the psychosocial risks factor (Table 7). Taking the moderately healthy group as reference, we notice that the two languishing subgroups display higher levels of psychosocial risks while the flourishing group has lower psychosocial risks (Fig. 2). The significance of these group differences is given in Table 7. The mental health class variable discriminates *absenteeism* between the languishing and flourishing group but not between the others. However, it



Note: MHC_G: General Mental health factor; EWB: Emotional Wellbeing; SWB: Social Wellbeing; PWB: Psychological Wellbeing

Fig. 1 Mental health classes from the bifactor ESEM latent factor analysis

discriminates *presenteeism* and *turnover intentions* between all the categories except the two languishing subgroups.

Latent Class (Profile) Regressions Each of the three psychosocial risks factors has been specified as a predictor of the mental health latent class before running latent profile analysis (an instance of *conditional* latent class analysis) on the mental health factor scores. We checked that the four-class profile resulting from this *conditional* latent class analysis is comparable to that of the *free* latent class analysis (except for slightly different size groups). The moderately mentally healthy category is used as reference, since it's the majority group. It is shown (Table 8) that the hedonic (emotional) languishers display a significantly higher probability for

Table 4 Predicting psychosocial risks from mental health (Structural Equation Modeling)

Outcome	Predictor: Wellbeing	Beta
Absenteeism	General MHC	−.10*
	Emotional	–
	Social	−.08*
	Psychological	–
Presenteeism	General MHC	−.26***
	Emotional	−.21***
	Social	−.10**
	Psychological	–
Turnover intention	General MHC	−.34***
	Emotional	−.15***
	Social	−.13**
	Psychological	−.18***

$*p < .05$; $**p < .01$; $***p < .001$; AVE**:** Average Variance Extracted

Table 5 Structural Equations Modeling Fit Indices

Model	Adj χ^2	df	p value	RMSEA	RMSEA 90% CI	CFI	TLI	SRMR	AIC	BIC	A-BIC
3F-PSR on Bi-ESEM	35.67	21	.024	.026	[.009–.040]	.993	.988	.017	23,332.49	23,481.61	23,386.32
Good Fit			> .05	≤ .06	[.000–.080]	≥ .95	≥ .95	≤ .080	Minimum	Minimum	Minimum

Adj χ^2: Adjusted chi-square; RMSEA: Root Mean Square Error of Approximation; CI: Confidence interval; CFI: Comparative Fit Index; TLI: Tucker-Lewis Index; SRMR: Standardized Root Mean Square Residual; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion; A-BIC: Adjusted BIC; 3F-PSR: Three-factor psychosocial risk; Bi-ESEM: Orthogonal bifactor exploratory structural equation modeling

Table 6 Latent class factor analysis of bifactor exploratory structural equation modeling

Model	Values					*p*-values	
	Log Likelihood	*AIC*	*BIC*	*A BIC*	*Entropy*	*LRT*	
2 classes	−5322.66	10,671.30	10,735.94	10,694.65	.78	<.001	<.001
3 classes	−5223.18	10,482.36	10,571.83	10,514.66	.74	<.001	<.001
4 classes	**−5150.44**	**10,346.88**	**10,461.21**	**10,388.16**	**.76**	**.02**	**.02**
5 classes	−5117.10	10,290.20	10,429.38	10,340.44	.79	.57	.58
6 classes	−5079.39	10,224.78	10,388.81	10,283.99	.81	.10	.10
7 classes	−5040.09	10,156.18	10,345.07	10,224.38	.81	.17	.18

AIC Akaike Information Criterion; *BIC* Bayesian Information Criterion; *A-BIC* Adjusted BIC; *LRT* Vuong-Lo-Mendell-Rubin Likelihood Ratio Tests (respectively non-adjusted and adjusted); Bold values line indicates the optimal number of classes

presenteeism (OR = 1.73). The eudaimonic (psychological) languishers exhibit a significantly higher probability for turnover (OR = 1.79), while the flourishers demonstrate a significantly lower probability to leave their job/organization (OR = .72). If one of the languishing class is taken as reference (e.g. the emotional languishers, Supplement 6), one can notice that the flourishers demonstrate a significantly smaller probability for presenteeism (OR = .53) and turnover intention (OR = .59). However, whereas the psychological languishers also display a lower probability for presenteeism (OR = .69), their probability for turnover intention is higher (OR = 1.45).

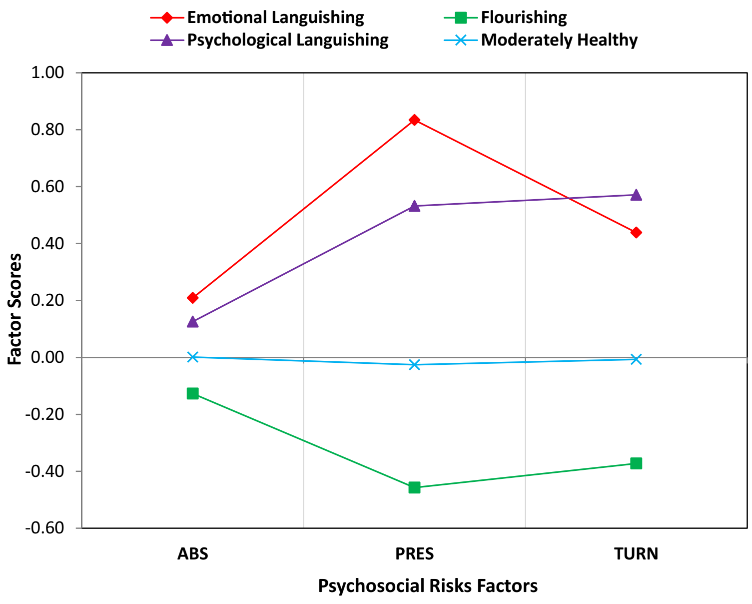
5.4 Decision Trees

Each step of the tree (Fig. 3) indicates that if the node condition is fulfilled then the left side of the tree node applies, otherwise it is the right side. For example, if MHCA6 equals 3.25 or greater, then the next step is to consider the value of MHCA12 compared to 3.50, otherwise the next step would be to consider the value of MHCA2 compared to 3.23. In examining the decision tree diagnosis algorithm, we notice that only half of the 14 items are required to

Table 7 One-way analysis of variance for psychosocial risks in the workplace (F-values)

Psychosocial risk		1. Flourishing (*N* = 279)	2. Moderately Healthy (*N* = 574)	3. Psychological Languishing (*N* = 114)	4. Emotional Languishing (*N* = 98)	Group Differences[a]
Absenteeism	Mean	−0.13	0.00	0.13	0.21	1–3**
	SD	0.66	0.76	0.87	0.91	1–4*
Presenteeism	Mean	−0.46	−0.03	0.53	0.83	1–2**
	SD	1.41	1.52	1.65	1.52	1–3***
						2–3**
						1–4***
						2–4***
Turnover intention	Mean	−0.37	−0.01	0.57	0.44	1–2**
	SD	0.95	1.05	1.06	1.00	1–3***
						2–3**
						1–4***
						2–4***

* p < .05; **p < .01; *** p < .001; [a] Bonferroni post hoc corrected



Note: ABS: Absenteeism factor; PRES: Presenteeism factor; TURN: Turnover Intention factor

Fig. 2 Comparing psychosocial risks levels between mental health classes

determine the class assignment of each observation, and after some simple optimization of the model, the average hit rate over one hundred predictions exceeds 90% (Fig. 3, Supplement 7).

6 Discussion

6.1 Factor Study and Variable Approach

Factor Structure Recently there has been renewed debates on the factor structure of the MHC-SF. Most contributors have questioned the validity of some aspects of the three-factor traditional Independent Cluster Model CFA, as this approach tends to bias the parameter

Table 8 Latent class regression estimations (ref. Moderately Mentally Healthy)

Mental health category	Psychosocial risk	Coef.	Odds ratio
Emotional languishing	Absenteeism	−.48	0.62
	Presenteeism	.55***	1.73
	Turnover intention	.21	1.23
Psychological languishing	Absenteeism	−.58	0.56
	Presenteeism	.17	1.19
	Turnover intention	.58***	1.78
Flourishing	Absenteeism	−.09	0.91
	Presenteeism	−.08	0.92
	Turnover intention	−.33**	0.72

*p < .05; **p < .01; ***p < .001

estimates, e.g. by inflating the correlations between the emotional wellbeing and psychological wellbeing or, more broadly, between the hedonic and the eudaimonic factors. As a remedy some authors advocate the use of exploratory structural equation modeling, which permits cross loadings (Joshanloo 2016a, b; Joshanloo et al. 2016) whereas others prefer bifactor models that include an overarching general factor, to account for additional variance (De Bruin and Du Plessis 2015; Hides et al. 2016; Jovanović 2015). Several recent studies, however, have demonstrated the bifactor exploratory structural equation modeling (Bi-ESEM) to be the best fitting model (Longo et al. 2017; Rogoza et al. 2018; Schutte and Wissing 2017; Silverman et al. 2018), and our current study based on a random sample of 1065 French workers concurs (Table 1, Supplement 1). The loadings and ω values of our Bi-ESEM model confirm the existence and prevalence of a strong general factor (G-factor), MHC_G. This fact supports the idea according to which mental health can be measured with an overarching underlying factor explaining much – if not most – of the covariance between all the 14 items of the MHC-SF. The G-factor score can therefore be used as a measurement of the overall *level* of mental health (Morin et al. 2017). However, there are some domain specific effects not explained by the G-factor that are explained by the S-factors. These S-factors explain the variance in the corresponding items, controlling for the G-factor, whereas the remaining unexplained variance is captured by the residuals. Hence, there is some variance of an *emotional* nature that is only due to emotional wellbeing and which cannot be captured either by the social wellbeing, the psychological wellbeing or the general factor. The related factor score could be described as a measurement of *pure emotional* effects. Similarly, we would associate the scores of social wellbeing and psychological wellbeing respectively to *pure social* and *pure psychological* effects. In other words, the emotional (EWB), social (SWB) and psychological (PWB) wellbeing factors encapsulate respectively the scores of emotional, social and psychological effects over and above their shared common variance of mental health (measured by the G-factor, MHC_G), discriminating each factor from all the others.

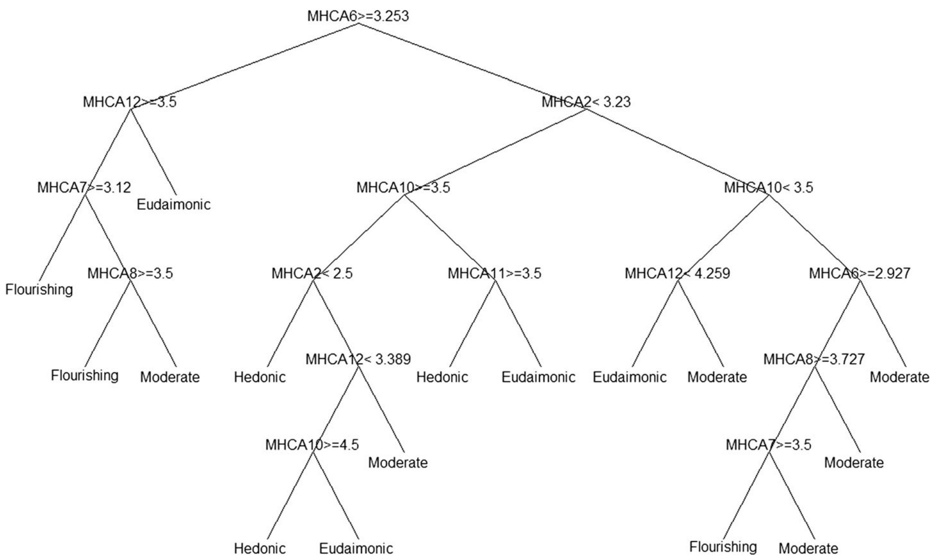


Fig. 3 Decision Trees and performance over 100 predictions

Nomological Validity One of the main benefits of using a bifactor model is the possibility of differentiating the general from specific effects in a nomological network (Chen et al. 2012, 2006; Sánchez-Oliva et al. 2017; Żemojtel-Piotrowska et al. 2018). We believe that the construct validity of the MHC-SF, and specifically that of the Bi-ESEM model will require more attention from a nomological perspective, because it has now been long admitted that "(…) to validate a claim that a test measures a construct, a nomological net surrounding the concept must exist. When a construct is fairly new, there may be few specifiable associations by which to pin down the concept (…)" (Cronbach and Meehl 1955, p. 12). To date, very few studies have addressed the nomological and criterion validity of the Bi-ESEM structure of the MHC-SF (Joshanloo and Niknam 2017; Strümpfer et al. 2009), hence it seems reasonable to postpone a definite conclusion regarding the factor structure of the MHC-SF without further exploration of this topic. In the current study, one must acknowledge that the general and specific factors have distinct contributions in predicting psychosocial risks in the workplace. Indeed, while the general factor is negatively associated to the three psychosocial risks factors, only social wellbeing is negatively associated to absenteeism, only psychological wellbeing is not negatively associated to presenteeism, while all the three domain-specific factors are negatively associated to turnover intentions. It should also be noted that the Bi-ESEM model exhibits a richer and more complete network of relationships with the psychosocial risks' factors than any of the competing models (Supplement 3). As Keyes (2007) has already highlighted, people who are flourishing display the best psychosocial functioning. This is a first confirmation through structural equations modeling.

6.2 Classification Study and Person-Centered Approach

Two Languishing Categories While the factor structure of the MHC-SF has received considerable research attention, its associated classification has rarely, if ever, attracted comparable interest. We used here a latent class analysis applied to the factor scores of the Bi-ESEM model – which is also called, latent confirmatory factor analysis, a member of the factor mixture models (Wang and Wang 2012). First, our results suggest that adopting a Bi-ESEM factor structure for the MHC-SF leads to more complex profiles of mental health than the three levels originally suggested by Keyes (2002, 2005) i.e. *languishing*, *moderately mentally healthy* and *flourishing*. It is most likely that a unidimensional model or even a model using the summated factor scores will lead to subgroups akin to Keyes's mental health categories. As a matter of fact, since the G-factor score express the overall level of mental health, in our study it does indeed discern only three levels: an average level (the moderately mentally healthy) gathering most of the respondents, an above-average level (the flourishing), and two indistinguishable below average levels (the languishing). In other words, the general factor sees only one languishing category. Yet, our study identifies two rather distinct profiles of languishing: those who have a low level of emotional wellbeing but a high level of psychological wellbeing – *the hedonic or emotional languishers*, and those who have a "normal" level of emotional wellbeing but a low level of psychological wellbeing – *the eudaimonic or psychological languishers* (Fig. 1).

Latent Class Analyses and Psychosocial Risks From a psychosocial risk perspective, our results lead to a second confirmation that those who are flourishing display the lowest level of psychosocial risks whilst those who are languishing exhibit the highest (Fig. 2, Table 7). Yet, from this point of view, there is no significant difference between the level of absenteeism, presenteeism and turnover intentions of the two languishing categories: no matter what type of languishing one has, it is not good for psychosocial functioning in the workplace. Still, conditional latent class analysis – also called latent class regression – provides a further insight as it informs us on how our psychosocial risks covariates determines our latent classes (Wang and Wang 2012; Wetzel et al. 2016). In fact, when covariates are present, it is recommended to conduct the latent class analysis *conditionally to* (i.e. predicted by) the covariates (Muthén 2004). Here, compared to the moderately mentally healthy, those who are in the hedonic languishing group are the most likely to demonstrate more symptoms of presenteeism, and those who are in the eudaimonic languishing group are the most likely to think about leaving their job or their company, while those who are in the flourishing category are significantly less likely to do so (Table 8). A notable result here is the difference between the two subgroups: the eudaimonic languishers are more likely to feel unhappy and envision turnover while the hedonic languishers are more likely to suffer from presenteeism (Supplement 6). This is a striking illustration of being unwell, yet at work, if not the sign of an ill-being due to an unbalanced emotional involvement (Aronsson and Gustafsson 2005; Baeriswyl et al. 2017; Hansen and Andersen 2008).

Diagnosing Mental Health From a clinical perspective, a simple decision tree (Fig. 3) paves the way to a quite reliable set of diagnostic rules to determine the most likely profile of an individual (90% accuracy). For example, an observation with MHCA6 (*Social Growth*) item response = 4 (2 or 3 times a week) or more, MHCA12 (*Personal Growth*) response = 4 or more, and MHCA7 (*Social Acceptance*) response = 4 or more will be assigned to the flourishing class. However even if MHCA7 response = 3 (once a week) or less, but MHCA8 (*Social Coherence*) response =4 or more, then this individual will also be diagnosed as flourishing. Clearly, the languishers are mostly characterized by a low value in MHCA6 (*Social Growth* = 3 or less) and a low value in MHCA2 (*Interest in Life*), and what differentiates the hedonic from the eudaimonic languishers diagnosis are the items MHCA11 (*Positive Relationship with Others*) and MHCA10 (*Environmental Mastery*) for which the hedonic subgroup have higher scores. Lastly, the moderately mentally healthy are mostly characterized by a high score in MHCA2 in addition to a low score in MHCA6.

Contributions From a managerial point a view, a human resource manager might be left wondering how she (he) could use the MHC-SF in her organization, for example to determine the profiles of their employees and assess their mental health as well as their likelihood to face adverse psychosocial risks. We recommend that she enroll their employees to fill in the questionnaire, then compute the individual and average score for each MCHA item over groups and subgroups or departments of her company. The decision tree is then applied to the averaged value of the relevant (sub)group. This estimation should be more reliable for assessing group mental health than first assigning each individual to a class, then summing over the (sub)groups. This is so because the individual scores are only integers, while the average score are ratios and will match more closely the nodes' split conditions.

This study is, to the best of our knowledge, amongst the very first to investigate the mental health of the French workers using the MHC-SF and to link absenteeism, presenteeism and turnover intention with mental health. It is also one of the first investigations on the empirical validity of Keyes's theoretical categories of mental health. Although our sample is not formally representative of the population of French workers, it is nevertheless a fairly broad sample of middle-class French workers in geographical and occupational terms (although employees are overrepresented) and so our findings are highly informative about the validity of the MHC-SF in French culture.

Study Limitations Our study is not without limitations. One of the main areas of future investigations lies in the optimal choice of computing parameters for the mixture or latent class analysis. For example, is it always reasonable to allow the means and variances to be simultaneously freely estimated or rather only the means but not the variance? In our case, constraining equality of variances on the latent classes has led to better results than estimating them freely. The latter has yielded theoretically unrealistic group sizes – or spurious classes – and contradicted the differentiated effects between the G-factors and S-factors shown in the variable approach. Another challenge is the possibility to fall on a local, rather than a global minimum in the algorithm, and reducing this risk requires increasing computational complexity, time and capacity, which may not always be possible nor practical, past a certain point.

Regarding the two types of languishers, there is a need to explore more thoroughly their stability and if so the difference in their functioning. We have shown here that while the *free* latent class analysis does not support a predictive difference – between the two subgroups – through analysis of variance on the outcome variables, the *conditional* latent class analysis does support some distinct relationships with the outcome variables through latent class regression. Only more studies using different samples as well as different outcome variables will shed more light on this topic.

Ours was a cross-sectional survey study and so the nomological network used in the structural equations modeling must be confirmed in quasi-experimental or longitudinal studies if causality is to be ascertained. Nevertheless, our findings are encouraging and open many avenues for study of the relationships between mental health and other organizational constructs such as work engagement and leadership, and other indicators of optimal functioning such as positivity, flow, character strengths, personal efficacy and motivation.

7 Conclusion

Person-centered study of the Keyes's mental health model has been scarce, as has been its application in an occupational context and in the French culture. We attempted here to remedy these shortcomings through a study combining a variable and person-centered approach of the mental health, on a diverse sample of French workers and including psychosocial outcomes. Given the increasing number of studies using the MHC-SF across nations and cultures it would be of a great interest to explore the extent to which our results generalize to other samples, and if not, what other types of profiles may arise from these studies. We also feel that future studies should dive more deeply into the nomological network of the mental health, and for practical purposes to explore in depth the reliability of the diagnostic instructions suggested here.

Compliance with Ethical Standards

Conflict of Interest The author declares that he has no conflict of interest.

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