Positive mental health in work and private life: Extending modeling to a data-driven approach

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POSITIVE MENTAL HEALTH IN WORK AND PRIVATE LIFE: EXTENDING MODELING TO A DATA-DRIVEN APPROACH

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Abstract

This research aims to extend the concept of positive mental health (PMH) as flourishing (Keyes, 2002) from a general context to specific work and non-work contexts. Conceptually, based on the integrated work-life balance framework (Sirgy & Lee, 2018), we explore the possibility that PMH in work life may be distinct from yet correlated with its counterpart in non-work life. Methodologically, we integrate several approaches. We analyze the multifaceted construct of PMH in such a way as to include and differentiate the general from the domain-specific expressions of PMH, using a person- and variable-centered approach, while accounting for the work and non-work contexts. Two different studies—respectively n=304 and n=1066—are used to explore the factor structure of this extended integrated construct of PMH. For each sample, a bifactor exploratory structural equation modeling (Bi-ESEM) provides the best fit to the data. Latent class analysis provides a means to explore different classes of PMH. A machine learning algorithm (classification trees) is used as an operational method to diagnose class assignment and to test classification predictive performance. Drawing on data from a sample of 1,066 French workers, our model reveals four classes of respondents, each displaying a particular profile of PMH in work-life contexts. Applying it to psychosocial functioning, we show that general and specific factors have significantly different associations with the reduction of psychosocial risks, and that there are significant differences between the profiles, wherein the full cross-context flourishers display the lowest level of absenteeism, presenteeism, turnover intentions, and work unhappiness, and the professional languishers the highest. We conclude that splitting PMH into work and non-work contexts highlights some significant facets and outcomes of the construct that are not available in its general expression alone. Machine learning proves to be an efficient and reliable way to diagnose and predict PMH with a high level of performance (accuracy=0.90, Kappa=0.86).

Keywords: bifactor modeling (ESEM), factor mixture analysis, machine learning, decision trees, work-life balance, flourishing, mental health

Résumé

Santé mentale positive au travail et dans la vie privée : extension de la modélisation à une approche inductive (centrée sur les données)

Cette recherche vise à étendre le concept de la Santé Mentale Positive (PMH) (Keyes, 2002) conçu comme épanouissement, d'un contexte général aux contextes spécifiques professionnel et privé. D'un point de vue conceptuel, à la lumière de la conception intégrée d'équilibre vie privée & vie professionnelle (Sirgy & Lee, 2018), nous explorons l'éventualité que les structures factorielles de la PMH entre vie privée et vie professionnelle puissent être corrélées, mais distinctes. En termes de méthodologie, nous intégrons plusieurs approches. Nous analysons le construit multidimensionnel de PMH en intégrant simultanément un facteur général et des facteurs spécifiques. Pour ce faire, nous nous appuyons sur une approche à la fois centrée sur les variables et sur les personnes, en tenant simultanément compte des contextes au travail et hors travail. Deux différentes études sont menées – d'échantillons respectifs de taille n=304 et n=1066 – pour explorer la structure factorielle de ce construit étendu et intégré de PMH. Pour chacune d'entre elles, une modélisation en équations structurelles exploratoires bifactorielle (Bi-ESEM) offre le meilleur ajustement aux données. Une analyse en classe latente permet d'explorer les différentes classes de PMH illustrant chacune une typologie différente de PMH dans un contexte professionnel-privé. Une méthode d'apprentissage supervisé (arbres de classification) est utilisée pour diagnostiquer efficacement l'attribution des individus à chaque classe. En s'appuyant sur ces résultats pour étudier le fonctionnement psychosocial, nous montrons qu'il existe une différence significative entre les profils, où ceux qui sont épanouis dans tous les contextes incarnent les niveaux les plus bas de risques psychosociaux, alors que ceux qui languissent au travail en incarnent les niveaux les plus élevés. Nous en concluons que la distinction entre PMH en contexte de travail et PMH hors travail éclaire des aspects du construit qui ne sont pas disponibles dans son expression générale seule. L'apprentissage supervisé (Machine Learning) s'avère être un outil fiable et efficace de diagnostic et de prédiction des classes de PMH, démontrant une importante performance prédictive (Taux de classification = 0.90, Kappa = 0.86).

Mots-clés : Modélisation bifactorielle (ESEM), Analyse factorielle de mélange, Apprentissage Supervisé, Arbres de Décision, Équilibre vie privée - vie professionnelle, Épanouissement, Santé Mentale

INTRODUCTION

Keyes (2002) defines positive mental health (PMH) as comprising positive feeling and positive functioning. Positive feeling is operationalized as emotional well-being (EWB), whereas positive functioning is operationalized as social well-being (SWB) and psychological well-being (PWB) (Keyes, 2002, 2007). These dimensions are measured with the Mental Health Continuum Short Form (MHC-SF). Using both a dimensional and a categorical DSM-like assessment, Keyes suggests that the presence of PMH is reckoned as *flourishing*, its absence deemed *languishing*, and those who are neither flourishing nor languishing are labeled *moderately mentally healthy*. Keyes (2005) shows that those mentally healthy adults display the best psychosocial functioning, such as having the fewest missed days of work, making minimal use of their health insurance, and being the least prone to major depressive episodes as well as to cardiovascular diseases.

Through Keyes's MHC-SF, the investigation of PMH has been conducted in many countries, on all continents, and the measurement model has been fairly consistent and invariant (Iasiello et al., 2022; Żemojtel-Piotrowska et al., 2018). The factor structure of the MHC-SF has been under debate for more than a decade, but there is a growing consensus that the best model would involve cross-loadings (exploratory structural equation modeling; ESEM) with three factors (EWB, SWB, and PWB), which may also involve a general factor (bifactor ESEM; Bi-ESEM). Recent multinational studies have confirmed the consistency of Bi-ESEM as the best fitting factor structure for the MHC-SF (Jaotombo, 2019; Longo et al., 2020; Piqueras et al., 2022). Thus, given its relevance in measuring and diagnosing PMH, it is reasonable to use it for studies in organizations or at least for understanding well-being and positive functioning in the workplace. Yet, such works remain scarce (Baylina et al., 2018; Jaotombo, 2019; Schröder, 2017).

Furthermore, to the best of our knowledge, all previous studies consider PMH only in a general context, and do not distinguish PMH in a professional context from PMH in a private context. Given the importance of understanding the dynamic between work and non-work life (Brough et al., 2020), we are interested in investigating to what extent the concept of flourishing is life-context specific. In other words, we decompose PMH into a professional component and a private component.

Additionally, despite the wide adoption of Keyes's diagnosis, we do not know but one study exploring to what extent these classes may be inductively retrieved from the data (Jaotombo, 2019). Besides, these diagnostics do not have any real counterpart when we account for professional and private PMH contexts. Hence the need to explore classes of integrated life-context PMH profiles and to build a related method of diagnosis.

This article aims to illustrate how several methodological approaches may be used to tackle these various connected interests. First, it demonstrates how a concept such as PMH may be considered context-dependent (professional vs. private life) and how an integrated factor structure may be used as a measurement model. Second, it uses an inductive, data-driven approach to explore classes of integrated work vs. non-work PMH profiles. Third, a machine learning algorithm is used to develop a diagnosis method and predict the new classes of professional vs. private PMH profiles.

The dual-continua model of mental health

The common knowledge in psychology was to consider that mental health and mental illness were opposite poles of the same continuum; this was known as the bipolar model. However, there is extensive evidence that mental health and mental illness are two different but correlated factors that define the dual-continua model (Iasiello & van Agteren, 2020; Keyes, 2005). In this latter case, one factor defines the mental illness dimension while the other defines the mental health dimension. A diagnosis based on the dual-continua model defines the complete state in mental health (Keyes, 2007, 2014), where an individual could respectively be mentally ill or not, on the one hand, and flourishing, moderately mentally healthy, or languishing, on the other. Despite the merit in investigating the complete state model, a very large majority of studies focus on PMH alone. Indeed, the debate around the factor structure of PMH has been rich and enlightening (Iasiello et al., 2022). Our goal is to take this debate one step further by examining PMH under an integrated work-life balance framework. Thus, we will focus only on the PMH dimension of the complete state model.

An integrated work-life balance framework

It is well known that work-life balance plays a major role in well-being and in overall satisfaction, which make up some of the dimensions of PMH (Keyes, 2002; Sirgy & Lee, 2018). From an integrative perspective, life satisfaction from a variety of life domains contributes uniquely to overall satisfaction (Rojas, 2006), and employees engaging in satisfactory work and non-work activities cumulatively will experience a higher level of satisfaction. This derives from the bottom-up spillover additive model, which posits that overall life satisfaction, or the overall contribution of positive affect, can be predicted by the contribution from each life domain (Sirgy & Lee, 2018). Furthermore, the integrative perspective suggests that work-life balance may also be approached through the principles of role enrichment (learning occurring in one life domain is transferred into another life domain) (Greenhaus & Powell, 2006), segmentation (preventing difficulties in one life domain from spilling over to another life domain improves life satisfaction), or compensation (compensating lack in one life domain with satisfaction from another life domain improves life satisfaction) (Sonnentag et al., 2008). These facts strongly suggest that the variance in PMH from one life domain is likely to add to or subtract from the variance from another life domain. It is therefore sensible to consider that PMH variance may be broken down into PMH variance contributions from different life domains. The following sections will outline some of the methods used in the literature that will support our exploration.

Bifactor exploratory structural equation modeling (Bi-ESEM)

A bifactor approach is appropriate whenever it is necessary to account for both a general factor and domain-specific factors (Reise, 2012). For example, the structure of the MHC-SF may involve a general factor (MHC) capturing PMH as an overarching concept, and three domain-specific factors, respectively EWB, SWB, and PWB (Iasiello et al., 2022).

Additionally, to avoid the inflation of correlations between factors—which deteriorates discriminant validity—cross-loadings should be welcomed but maximized on the target items and minimized on the non-target items. For example, whereas each item of the MHC-SF should be allowed to load on all of the factors, the items theoretically associated with emotional well-being should be maximized on the EWB factor and minimized on PWB and SWB (Joshanloo, 2020; Marsh et al., 2009). However, all the factors should be freely loading on the general factor MHC, if there is one.

It has been consistently shown that Bi-ESEM yields the best fit to the MHC-SF factor structure (Longo et al., 2020). Here, we want to explore to what extent PMH may be broken down into two distinct but correlated Bi-ESEM constructs, each measuring PMH in each life domain. Thus, our first research question is as follows:

What factor structure would accommodate an integrated model of work vs. non-work PMH?

Construct validity

Construct validity may be defined as the extent to which a measurement model accurately assesses the corresponding theoretical construct. It involves the ascertainment of other types of validity such as convergent validity, discriminant validity, and criterion or predictive validity (Gerbing & Anderson, 1988; O'Leary-Kelly & Vokurka, 1998).

Convergent validity. This is the extent to which each factor explains more variance than the residuals. The proportion of total variance explained by each factor, or average variance extracted (AVE), should be greater than 0.5 (Fornell & Larcker, 1981; Hair et al., 2018).

Reliability. This is a measure of the extent to which the scores in the test items can be attributed to "true" variations rather than to errors or random variations. The omega index used to measure reliability should be greater than 0.7 (Morin et al., 2018).

Discriminant validity. The variance between the factors (their squared correlations) should not be greater than their AVEs. In the case of PMH in the two life domains (work vs. non-work), the variance between the factors of each context should be smaller than their AVEs. For example, the squared correlation between professional and private EWB should be smaller than each of their respective AVEs (Fornell & Larcker, 1981; Hair et al., 2018).

Predictive validity. This determines to what extent the measurement model is capable of retrieving results predicted by the theory. For example, the theory predicts that those flourishing individuals should display a higher level of psychosocial functioning or a lower level of psychosocial risk (PSR). There are different ways of testing predictive validity, the most common being structural equation modeling (Hair et al., 2018; Kline, 2015). In this case, the factors' scores are used to predict the outcomes of interest (e.g., the PSR indicators) through a linear regression model. Another way of proceeding is to apply a class analysis based on the factor structure scores and to compare the emerging classes (or typologies) on the values of the outcomes of interest, such as the different PSR indicators or scores (ANOVA) (Wang & Wang, 2012). Our second research question is as follows:

Does the retained integrated work-life factor structure meet the basic criteria for construct validity as defined here?

Latent class analysis

There has been renewed interest in this topic, especially since the development of the so-called variable- and person-centered approach (Morin et al., 2017). The idea is to explain the variation in factor scores not only from the factor structure but also from existing differences within the groups of the population. Whereas Keyes's PMH theory defines three clearly different groups based on their items' scores (Keyes, 2002), if the theory is sound then a classification approach should be able to recover these to a large extent. Our third research question is as follows:

Are there specific profiles of PMH emerging from the integrated work-life factor model other than the three levels originally predicted by the PMH theory?

Machine learning: A brief conceptual summary

A recent systematic review has concluded that machine learning (ML) is increasingly making its way into human resource management (Garg et al., 2021). There are two families of ML that interest us: supervised and unsupervised learning.

Consider a data set with a relevant outcome variable and predictors . In essence, ***supervised learning*** refers to a set of approaches to estimate an unknown function (James et al., 2013) expressing the relationship between and . Supervised learning can be divided into two categories: in the case where is quantitative, we refer to a regression, and in the case where is categorical, it is called a classification. The main goal in supervised learning is to maximize prediction performance without sacrificing interpretability (Carvalho et al., 2019; Doshi-Velez & Kim, 2017).

When the outcome variable is absent, we are dealing with ***unsupervised learning***. The challenge then is to find patterns of relationships between predictors (correlations) or between instances (similarities). This makes it possible to group the most “related” variables, for example by extracting as much information as possible from the data points (principal component analysis) or to group observations by similarity (clustering). Latent class analysis may be considered as a subset of unsupervised learning.

One of the challenges following a latent class analysis is to predict the class to which a new instance belongs. This can be accomplished through machine (supervised) learning.

Our last research question is thus as follows:

To what extent is a machine learning model able to reliably predict classes of integrated professional vs. private life PMH?

METHODS

Samples

Sample 1. Data was collected from an online survey of a French convenience sample described in Appendix 2.

Sample 2. Data was collected from an online survey of a French random sample described in Appendix 3.

Measures

PMH was measured using the Mental Health Continuum Short Form (MHC-SF). The MHC-SF contains 14 items among which the first three items measure EWB, the five following items measure SWB, and the last six items measure PWB. Participants responded to a monthly six-modality frequency scale ranging from 1) *never*, 2) *once or twice*, 3) *about once a week*, 4) *two to three times a week*, 5) *almost every day*, to 6) *every day.* To account for work-life balance, each item of the MHC-SF is used twice: in a work (professional) context and in a non-work (private) context (see Appendix 1).

A three-factor CFA model is used to measure psychosocial risks. Hence, based on previous works (Aronsson et al., 2000; Gosselin et al., 2013; Johns, 2008), *presenteeism* is measured here by two items: "over the last 6 months, how often monthly did you go to work despite your being physically unable to work?" (PhysPres), and "over the last 6 months, how often monthly did you go to work despite your being psychologically unable to work?" (PsycPres).

Turnover intentions are measured by the following items: "over the last year, how often have you thought of changing to another job?" (Turnover), and "over the last year, how often have you thought that you did not feel well in your job?" (Unhappy).

Absenteeism was measured by two items: "over the last year, about how often did you miss work?" (GenAbs), and "over the last year, about how often did you miss work due to management?" (ManAbs).

Bifactor ESEM model specification

We shall study here a double Bi-ESEM model (Longo et al., 2020; Morin et al., 2017; Rodriguez et al., 2016), which means that we will specify one general factor and three specific factors for each life context. The analysis is carried out under Mplus 8.7 (Muthén & Muthén, 2021). WLSMV estimation is used to account for the responses to ordinal items (Morin et al., 2017). Building on previous results using the MHC-SF (Jaotombo, 2019; Longo et al., 2020), additional specifications are applied to the integrated model (details are shown in Figure 1 and in the codes in Appendix 1):

Construct validity specification

The factor structure of the integrated work and non-work Bi-ESEM model is examined for the two samples, including their fit indices, convergent validity, reliability, and discriminant validity. The latter is essential to confirm the empirical distinction between work and non-work contexts.

However, given that relevant outcomes are available only for the larger sample (n=1066), it is used for predictive validity and latent class analysis.

Latent class analysis specification

Given a well-fitted integrated work and non-work factor structure for the MHC-SF, we apply latent class modeling on the corresponding aggregated factor score (average of the items' loading on each factor) (Hair et al., 2018). In our modeling, we specify an increasing number of classes until either the (adjusted) LMR LR (Lo et al., 2001; Vuong, 1989) and/or the BLR tests (McLachlan, 1987; McLachlan & Peel, 2000) are non-significant, or the model fails to converge. After examining if the number of classes retained is pertinent and sensible, we retain the model that meets most of those requirements and has the lowest values in the fit indices (AIC, BIC, aBIC) and the highest values in log likelihood and relative entropy (Wang & Wang, 2012).

Diagnosing profiles of positive mental health with machine learning

From a practical standpoint, a straightforward method to diagnose PMH from the respondents' items' scores is required. To this end, we chose a decision tree technique, based on Breiman's (1984) classification and regression trees (CART). This is an algorithm of the ML family. The quality of the diagnosis (classification performance) is assessed by splitting the data set into a training sample—on which the model is trained—and a hold-out sample on which the model is tested (James et al., 2013). This process may then be applied over, for instance, 100 resampling over which an average performance is computed (Cawley & Talbot, 2010). The decision tree built by CART is highly interpretable and diagnostic-like (Doshi-Velez & Kim, 2017), which makes it ideal for PMH diagnosis (Strobl et al., 2009).

RESULTS

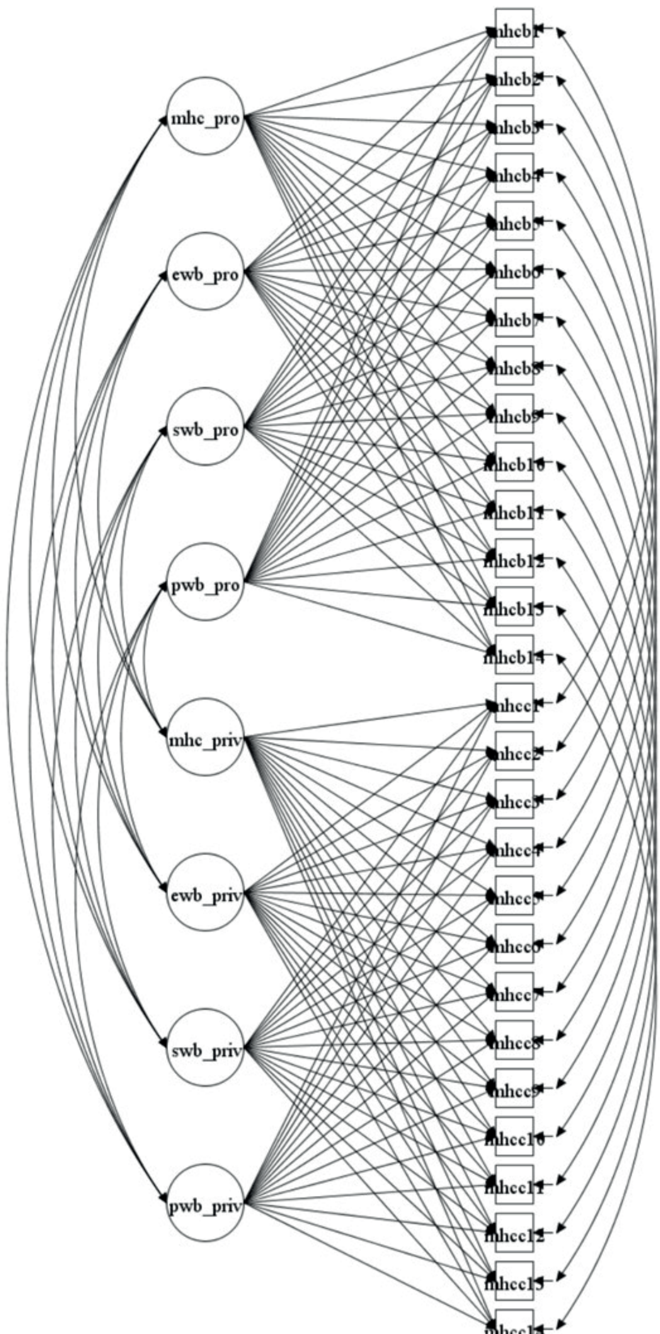
Bifactor ESEM measurement model

Sample 1. To avoid large residual errors and discriminant validity issues, the original model (Figure 1) is respecified by removing items 8 and 10. The model fit is excellent (RMSEA=0.033 [0.09-0.044]; CFI=0.994; TLI=0.980; SRMR=0.019).

Table 1-1. Sample 1: Convergent validity of the initial bifactor model (items 8 and 10 removed)

	ω	**AVE**
MHC_PRO	0.950	0.663
EWB_PRO	0.917	0.788
SWB_PRO	0.878	0.658
PWB_PRO	0.863	0.591
MHC_PRIV	0.939	0.633
EWB_PRIV	0.900	0.754
SWB_PRIV	0.846	0.609
PWB_PRIV	0.859	0.580

Figure 1. Initial bifactor ESEM model



Convergent validity. As illustrated inErreur ! Source du renvoi introuvable.

Discriminant validity. As one can see in Table 1-2, the shared variance of all specific factors across life contexts is smaller than (or equal to) their corresponding AVEs (Table 1-1). Thus, we can accept discriminant validity.

Table 1-2. Sample 1: Shared variance between general and specific factors

	Professional				Private			
(cor)²	**MHC_Prof**	**EWB**	**SWB**	**PWB**	**MHC_Priv**	**EWB**	**SWB**	**PWB**
MHC_Prof	—				0.415			
EWB		—				0.355		
SWB			—				0.389	
PWB				—				0.578
MHC_Priv	0.415				—			
EWB		0.355				—		
SWB			0.389				—	
PWB				0.578				—

Any squared correlation smaller than 0.100 is omitted.

Sample 2. As in sample 1, the original model (Figure 1) is respecified by removing items 4 and 5. The model fit is excellent (RMSEA=0.041 [0.036-0.045]; CFI=0.994; TLI=0.989; SRMR=0.016).

Convergent validity. As illustrated inErreur ! Source du renvoi introuvable.

Table 2-1. Sample 2: Convergent validity of the initial bifactor model (items 4 and 5 removed)

	ω	**AVE**
MHC_PRO	0.903	0.728
EWB_PRO	0.749	0.838
SWB_PRO	0.749	0.650
PWB_PRO	0.844	0.712
MHC_PRIV	0.900	0.731
EWB_PRIV	0.749	0.837
SWB_PRIV	0.745	0.660
PWB_PRIV	0.845	0.714

Discriminant validity. As shown in Table 2-2, and like in sample 1, we can accept discriminant validity.

Table 2-2. Sample 2: Shared variance between general and specific factors

	Professional				Private			
(cor)²	**MHC_Prof**	**EWB**	**SWB**	**PWB**	**MHC_Priv**	**EWB**	**SWB**	**PWB**
MHC_Prof	—				0.320			
EWB		—				0.378		
SWB			—				0.576	
PWB				—				0.579
MHC_Priv	0.320				—			
EWB		0.378				—		
SWB			0.576				—	
PWB				0.579				—

Any squared correlation smaller than 0.100 is omitted.

Three-factor psychosocial risk (PSR) measurement model

Sample 2. Here, the adopted model is a classic three-factor CFA (Figure 2). The measurement model displays an excellent fit (RMSEA=0.028 [0.000-0.053]; CFI=0.997; TLI=0.993; SRMR=0.012).

Convergent validity is assured as all the omega values are greater than 0.7 and the AVEs are all greater than 0.5.

Discriminant validity is also ensured given that the highest shared variance is smaller than the smallest AVE.

Table 3. Convergent validity of the three-factor CFA model

ω	0.711	0.854	0.875
AVE	0.565	0.747	0.778

Table 4. Shared variance of the three-factor CFA model

Factors	ABS	PRES	TURN
ABS	—		
PRES	0.162	—	
TURN	0.075	0.295	—

Predictive validity. The theory suggests that work-life flourishing should predict negative associations with psychosocial ill-functioning such as absenteeism, presenteeism, and turnover. We examine those predictions through structural equation modeling where the three PSR factors are regressed on the six factors of the Bi-ESEM model (RMSEA=0.025 [0.021-0.029]; CFI=0.989; TLI=0.983; SRMR=0.021).

Figure 2. Three-factor CFA psychosocial risk model

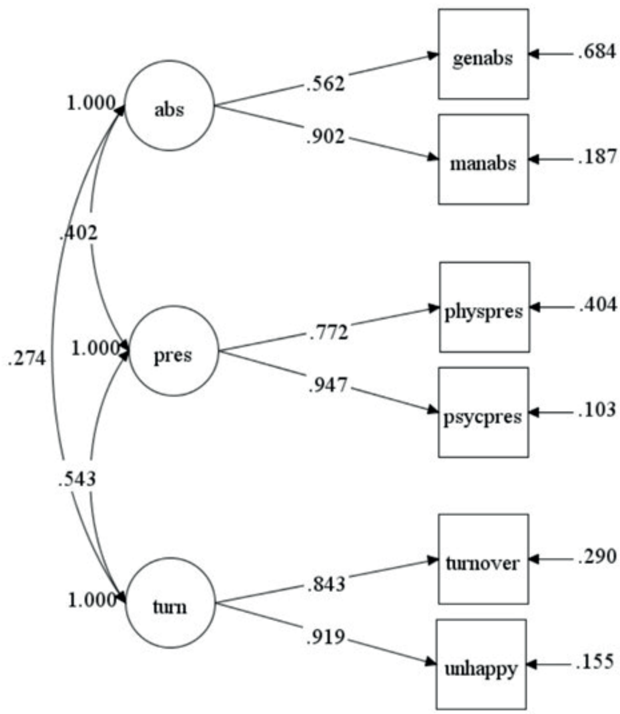


Table 5. Predicting psychosocial risks from work-life flourishing

OUTCOME	PREDICTORS	BETA		R²
ABS	MHC_PRO	-0.341	***	0.136**
	MHC_PRIV	0.193	**	
PRES	MHC_PRO	-0.452	***	0.246***
	MHC_PRIV	0.113	*	
	EWB_PRIV	-0.174	**	
TURN	MHC_PRO	-0.735	***	0.535***
	EWB_PRO	-0.304	***	
	MHC_PRIV	0.146	**	

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

Contrasted effects between the professional and the private spheres. The significant effects of the *professional* MHC factors are indeed associated with a decrease in all of the PSR factors (with moderate to large effect size). However, except for the private emotional well-being factor, all the significant effects of the *private* MHC factors are associated with an increase in the PSR factors (with small effect size). Thus, flourishing in the private sphere predicts an increase in absenteeism, presenteeism, and turnover intentions, contrary to flourishing in the professional sphere (Table 5).

Classification through mixture analysis

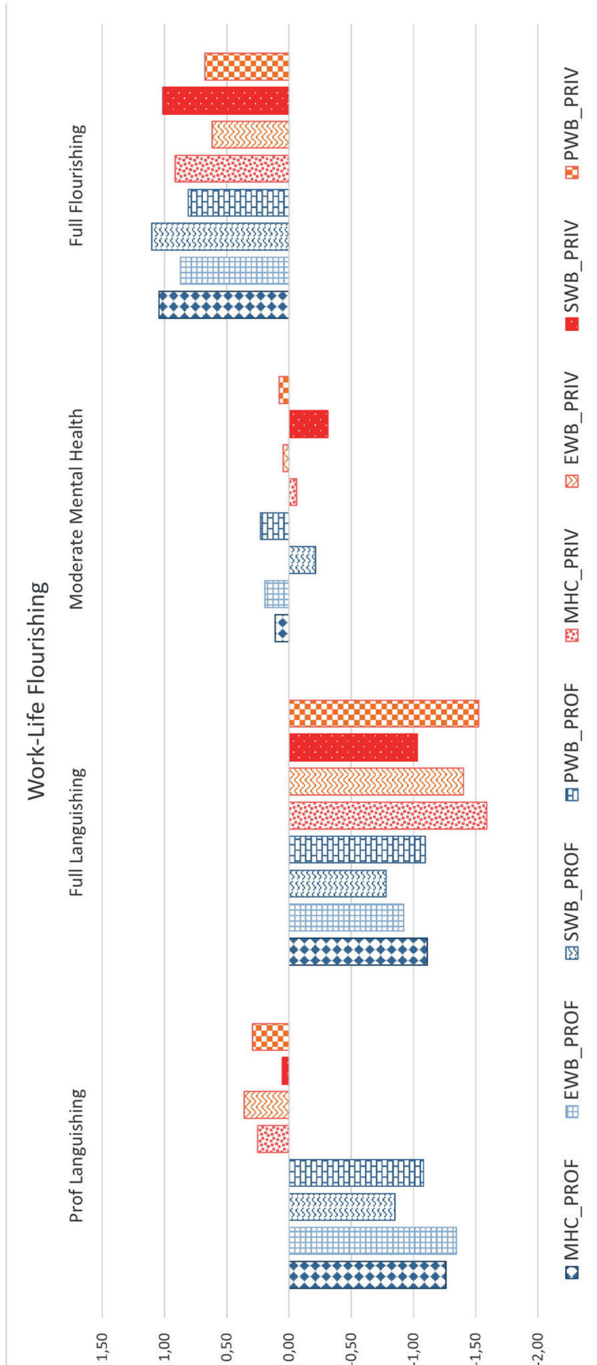
In the following, the aggregated items of the Bi-ESEM model are used as an input for latent class analysis. After several explorations, there remains a four-class or a five-class model (Table 6). However, the four-class model leads to a clearer interpretation with a higher relative entropy. From a theoretical perspective, we should keep in mind that mixture analysis may display extra spurious classes to account for the non-normality of the latent factors' distribution (Lubke & Muthén, 2005; McCrea, 2013; Sen et al., 2016). Hence, the rule of parsimony encourages us to choose the four-class model, which also yields the best theoretical interpretation.

Table 6. Latent class analysis of bifactor ESEM factors

	Values					p-values	
Model	**Log likelihood**	**AIC**	**BIC**	**aBIC**	**Entropy**	**LRT**	
2 classes	-11805.003	23660.006	23784.298	23704.893	0.892	0.0000	0.0000
3 classes	-11133.659	22335.318	22504.355	22396.365	0.897	0.0000	0.0000
4 classes	-10660.338	21406.676	21620.458	21483.882	0.907	0.0007	0.0007
5 classes	-10384.653	20873.307	21131.833	20966.672	0.900	0.0343	0.0363
6 classes	-10197.98	20517.961	20821.232	20627.485	0.892	0.4750	0.4788

Figure 3 presents the profiles of the four classes of work-life flourishing retained when we standardize the items' scores over each factor across contexts (mean=0, standard deviation=1). While we can recognize the three levels of mental health initially theorized by Keyes (2002), we also notice some new results. The highest class describes those who are fully flourishing across life contexts: in work as well as in private life (above average scores). Then come those who are moderately mentally healthy across life contexts (average scores) and those who are languishing across life contexts (below average scores). However, there is a new category of people who are obviously languishing in the professional arena while being more than moderately mentally healthy in the private sphere.

Figure 3. Profiles of work-life flourishing



Comparing the average absenteeism, presenteeism, and turnover intention levels, we also notice that the professionally languishing class demonstrates significantly higher values on all PSR indicators than the other classes, and the lowest values are displayed by the fully flourishing class (Figure 4, Tables 7 to 9). The four classes of respondents have significantly distinct levels of PSR for each factor except for absenteeism, where only the professionally languishing is above the others.

Figure 4. Comparing psychosocial risk levels

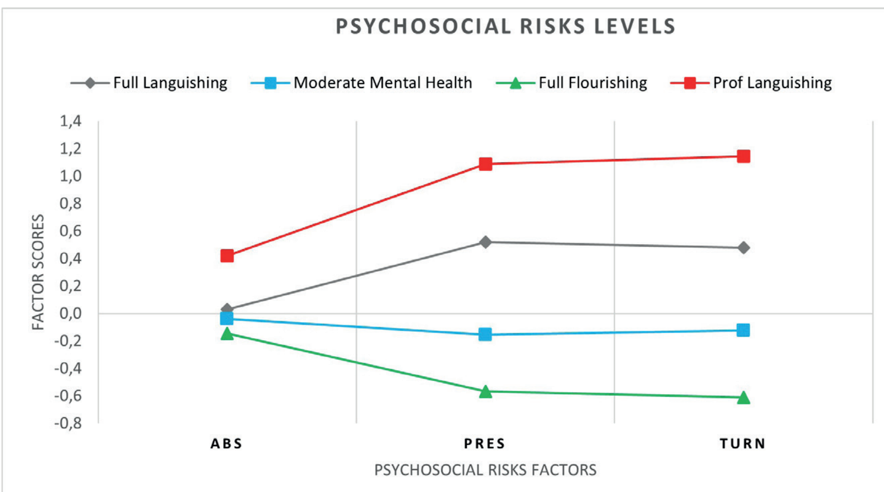


Table 7. Comparing absenteeism levels for profiles of work-life flourishing

ABS	Prof languishing	Full languishing	Moderate mental health	Full flourishing
Prof languishing	—	0.391***	0.458***	0.565***
Full languishing	0.391***	—	0.067	0.174
Moderate mental health	0.458***	0.067	—	0.107
Full flourishing	0.565**	0.174	0.107	—

Post hoc tests (absolute values, Bonferroni corrected). ***p-value<0.001, **p-value<0.01, *p-value<0.05

Table 8. Comparing presenteeism levels for profiles of work-life flourishing

PRES	**Prof languishing**	**Full languishing**	**Moderate mental health**	**Full flourishing**
Prof languishing	---	0.569**	1.244***	1.656
Full languishing	0.569**	---	0.674***	1.086

PRES	Prof languishing	Full languishing	Moderate mental health	Full flourishing
Moderate mental health	1.244***	0.674***	---	0.412***
Full flourishing	1.656**	1.086***	0.412***	---

Post hoc tests (absolute values, Bonferroni corrected). ***p-value<0.001, **p-value<0.01, *p-value<0.05

Table 9. Comparing turnover levels for profiles of work-life flourishing

TURN	Prof languishing	Full languishing	Moderate mental health	Full flourishing
Prof languishing	—	0.665***	1.269***	1.755***
Full languishing	0.665***	—	0.604***	1.090***
Moderate mental health	1.269***	0.604***	—	0.486***
Full flourishing	1.755***	1.090***	0.486***	—

Post hoc tests (absolute values, Bonferroni corrected). ***p-value<0.001, **p-value<0.01, *p-value<0.05

Categorical diagnosis through classification trees

Decision trees are used to predict respondents' class of work-life PMH based on their aggregated items' scores. After 100 resampling of the data (Sample 2) into training sets and test sets, the tuned decision tree model reaches a very good level of average performance and reliability (accuracy = 0.90, Kappa = 0.86) (see McHugh, 2012). The decision tree cut values are given in Figure 5 (left=YES, right=NO). As one may notice, among the eight average score values, only three are required for the diagnosis. Thus, the most discriminating factors are MHC_Prof, MHC_Priv, and SWB_Priv.

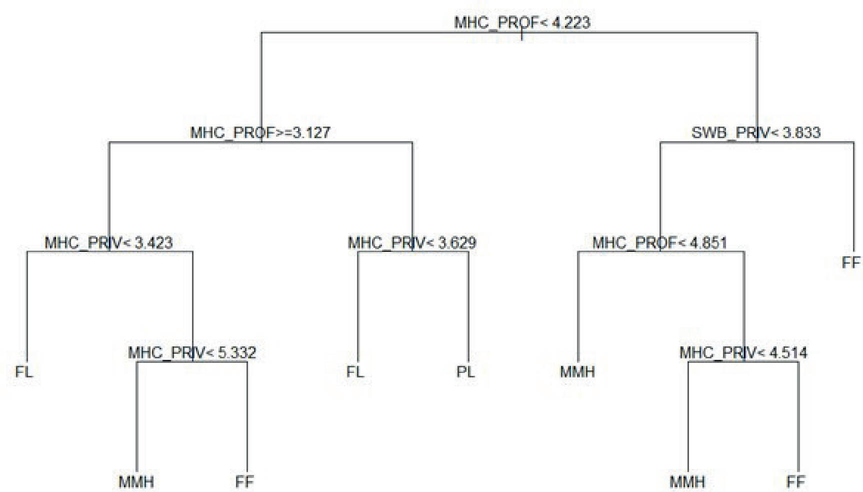
The legend for the classes is given as follows: FF stands for Fully Flourishing across contexts, MMH for Moderately Mentally Healthy across contexts, FL for Fully Languishing across contexts, and PL for Professionally Languishing.

DISCUSSION

PMH is life-context-specific. There have been some attempts to illuminate how PMH may generate positive outcomes in organizations (Bedin & Zamarchi, 2019; Colbert et al., 2015; Diedericks & Rothmann, 2013; Schutte & Loi, 2014). Most of these studies have focused on a general concept of PMH. Our results suggest that there may be some added value in studying PMH as a context-specific construct.

First, our model demonstrates that work and non-work PMH can be modeled as a double Bi-ESEM model specifying one general factor and three domain-specific factors for each life context. Putting aside some unsystematic errors due to the sample size and other specificities of the respondents, the very good fit and construct validity across samples confirm the stability of the retained measurement model. This means that there are aspects of work PMH that are not captured in non-work PMH. In the same way as PMH contains three distinct but correlated dimensions (EWB, SWB, PWB), overall PMH could also be considered as the "cumulated" contributions of PMH from several life domains such as work and non-work (Rice et al., 1985; Sirgy & Lee, 2018) which are distinct but correlated.

Figure 5. Decision tree for the work-life flourishing classes



Secondly, our model demonstrates the existence of four categories of work-life flourishing. While three of them seem to match Keyes's three levels of PMH—flourishing, moderately mentally healthy, and languishing (Keyes, 2002)—the fourth category describes a profile of respondents that we have labeled "the professionally languishing," as these are the people who are the most likely to display high levels of absenteeism, presenteeism, and turnover intentions. In the integrative work-life balance framework, this result relates closely to the principle of compensation, which posits that a person experiencing dissatisfaction in one life domain increases his level of engagement in another domain to enhance satisfaction in that domain (Freund & Baltes, 2002; Sirgy & Lee, 2018). Translated to our case, the dissatisfaction manifests as PSR in the workplace, and the compensation is expressed as a greater engagement resulting in flourishing in the non-work sphere. The more difficult the work experience becomes, the more people will compensate by removing much of their (constructive) energy from work (absenteeism, turnover) to invest it into their non-work life and thus improve it, or even flourish in it.

Another interesting result is in line with previous findings: those who are fully flourishing, i.e., displaying high levels in all factors across work-life contexts, are also those who demonstrate the lowest levels of PSR (Keyes, 2007). This result supports the principle of positive affect spillover, which posits that positive spillover across life domains contributes to overall life satisfaction (Edwards & Rothbard, 2000; Sirgy & Lee, 2018), but extends it to the more integrative construct of PMH.

Thirdly, one must notice the striking results affirming that while the professional factors predict medium to strong effects in reducing psychosocial ill-functioning, the private factors, on the other hand, predict a slight increase in psychosocial ill-functioning. While this finding seems to fall within the work-life spillover compensation umbrella (Brough et al., 2020; Guest, 2002; Kelliher et al., 2019), the mechanism is new and original. Indeed, previous research has shown that flourishing is associated with a decrease in psychosocial ill-functioning, whereas languishing is associated with an increase thereof (Diedericks & Rothmann, 2013; Jaotombo, 2019; Keyes, 2007). However, these studies were conducted within a general context, not accounting for differentiated contributions from work and non-work life. Separating the variance due to the work and non-work contexts suggests that unless workers are flourishing in their professional life, their flourishing only in their private life may be associated with greater PSR.

All in all, the four profiles of work-life PMH seem to illustrate rather convincingly two of the theoretical principles linking work-life balance and overall life satisfaction: positive, moderate, and negative ***spillover*** are respectively illustrated by the fully flourishing, moderately mentally healthy, and fully languishing profiles across life domains; while ***compensation*** is illustrated by the professionally languishing profile.

On the other hand, although causality cannot be implied by this study, which is exploratory and cross-sectional, the variance explained by our measurement model in predicting several of those aspects of psychosocial ill-functioning is significant (Table 5). In other words, if managers are interested in reducing missed days of work, presenteeism, and turnover intentions, they may as well explore ways to increase flourishing in professional life, which most likely will require a change in organization, in management, and possibly in leadership (Biggio & Cortese, 2013; Karp & Helge, 2008; Kavanagh & Ashkanasy, 2006). Counting on workers to flourish on their own initiative outside of work is very unlikely to have any positive impact on PSR if nothing is done in the workplace itself. Consequently, interventions and measures aimed at improving the work-life flourishing of workers are most likely to yield positive results if they take place in a work context (Schulte et al., 2015). Nevertheless, should such interventions be successful in improving professional PMH, there should also be a significant increase in private PMH. How this happens is as yet unclear:

Does it suggest that the professional context will automatically impact the private context? The positive spillover principle would certainly be a credible explanation. Or, rather, does it imply that full flourishing must include both a professional initiative (most likely organizational) and a personal initiative? We tend to agree with the latter argument, as it would confirm other studies in PSR change management (Fredrickson et al., 2008). Indeed, even if the organization offers conditions and opportunities to facilitate flourishing in the workplace, it is also up to the workers to seize upon them and make the most of them (Jaotombo, 2013).

Methodology matters. When using latent variable modeling such as structural equation modeling, the measurement models used are paramount in determining the type of results obtained. It has been extensively demonstrated that when the measurement models are multidimensional constructs, then the traditional CFA measurement model (independent clusters model – ICM CFA) used in most management research is not very reliable, and that ESEM is a much better alternative (Marsh et al., 2014; Morin et al., 2016). In addition, if one wishes to differentiate between the general effect of such a multidimensional construct and its domain-specific factors, then a bifactor measurement model is much better than a second-order hierarchical model, not only in fitting the data better but also in opening up more possibilities for studying nomological networks (Alamer, 2022; Chen et al., 2006, 2012). Thus, Bi-ESEM is often one of the best options as a multidimensional measurement model.

Furthermore, recent studies have demonstrated that some of the unexplained variance in a model may come from the existence of homogeneous subgroups that are unaccounted for (Morin et al., 2017). This can be captured through latent class (or factor) analysis.

Lastly, in practice, for example in HR management, based on the responses to the items, some may appreciate having simple rules to assign individuals into subgroups that are easy to manage, and to which they may develop customized policies. With the era of artificial intelligence and big data, these rules may be automatized through machine learning approaches (Huang et al., 2020). Decision trees are a simple way of doing this, and we have given here a simple example of a rule set (Figure 5) with a good level of performance. We may also choose other algorithms to improve our classification performance, but we are then likely to lose information on the decision rules and fall into the black box problem (Guidotti et al., 2018). Future studies will focus on using machine learning algorithms to diagnose classes of PMH using variable importance and other approaches of explainable artificial intelligence (Linardatos et al., 2021).

This research has several limitations. At a purely computational level, if we had chosen to apply latent class analysis on the Bi-ESEM factor scores themselves, our analysis would yield different insights. So, as we see here once again, methodology matters. Regarding the classes themselves, the reliability of our diagnostic method remains to be explored, tested, and validated. Its dependability is largely based on the class assignment given by our sample. Hence, further study is required with "representative" samples as well as with samples from other cultures. Moreover, given the exploratory nature of our study, the use of a cross-sectional approach is appropriate. However, were we to study the determinants, causes, and consequences of work-life flourishing, these results would need to be compared with actual field practice in clinical or organizational settings. This may be accomplished using other data sources such as organizational records and longitudinal studies. Lastly, if this technology were to be automatized and deployed in the information systems of an organization, it is likely to raise several legal and ethical issues, not the least of which is data privacy and various types of bias (technical, cultural, etc.), which are beyond the scope of this article.

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APPENDIXES

APPENDIX 1

MHC-SF items adapted from Keyes (2014)

During the past month, how often did you feel …	MHCB	MHCC
1. happy	in your professional life	in your private life
2. interested in life	in your professional life	in your private life
3. satisfied with life	in your professional life	in your private life
4. that you had something important to contribute to society	in your professional life	in your private life
5. that you belonged to a community (like a social group, school, or neighborhood)	in your professional life	in your private life
6. that our society is becoming a better place	in your professional life	in your private life
7. that people are basically good	in your professional life	in your private life
8. that the way our society works made sense to you	in your professional life	in your private life
9. that you liked most parts of your personality	in your professional life	in your private life
10. good at managing the responsibilities of your daily life	in your professional life	in your private life
11. that you had warm and trusting relationships with others	in your professional life	in your private life
12. that you had experiences that challenged you to grow and become a better person	in your professional life	in your private life
13. confident to think or express your own ideas and opinions	in your professional life	in your private life
14. that your life has a sense of direction or meaning to it	in your professional life	in your private life

Data sets and codes used for this research are available on github: https://github.com/jaotombo/PMH_Work-Life_BI_ESEM

APPENDIX 2

Descriptive statistics of sample 1 (n=304)

		Counts	Percentage
Sex	Female	192	63.16%
	Male	112	36.84%
Family status	In a couple	205	67.43%
	Separated/divorced	58	19.08%
	Single	41	13.49%
Company size	1 to 10 employees	90	29.61%
	10 to 49 employees	69	22.70%
	50 to 249 employees	61	20.07%
	500+ employees	60	19.74%
	250 to 499 employees	24	7.89%
Education level	5 or more years of higher education (+Bac +5)	121	39.80%
	4 years of higher education (Bac +4)	56	18.42%
	3 years of higher education (Bac +3)	51	16.78%
	2 years of higher education (Bac +2)	45	14.80%
	High school diploma (Bac)	22	7.24%
	Middle school certificate (Pré-Bac)	9	2.96%

APPENDIX 3

Descriptive statistics of sample 2 (n=1066)

		Counts	Percentage
Sex	Female	607	56.94%
	Male	459	43.06%
Family status	In a couple	778	72.98%
	Single	288	27.02%
Professional status	Employee	959	89.96%
	Self-employed	59	5.53%
	Transition < 1 year	48	4.50%
Work contract	Full-time	825	77.39%
	Weekly contract	97	9.10%
	Part-time	60	5.63%
	Do not know	55	5.16%
	Fixed number of working days, full-time (forfait temps plein)	19	1.78%
	Fixed number of working days, part-time (forfait mi-temps)	10	0.94%
Income	€11,901 to €26,490	623	58.44%
	€26,491 to €70,900	204	19.14%
	€6,000 to €11,900	130	12.20%
	< €6,000	98	9.19%
	€70,901 to €150,000	7	0.66%
	> €150,000	4	0.38%

		Counts	Percentage
Education level	3 years of higher education	385	36.12%
	2 years of higher education	255	23.92%
	CAP/BEP (vocational certificate)	207	19.42%
	4 years of higher education	175	16.42%
	Without a high school diploma or middle school certificate	33	3.10%
	Master's degree or higher	11	1.03%
Company size	2,000+ employees	278	26.08%
	< 10 employees	220	20.64%
	10 to 49 employees	166	15.57%
	50 to 199 employees	161	15.10%
	500 to 2,000 employees	123	11.54%
	200 to 499 employees	118	11.07%
Manager status	None	755	70.83%
	Middle	255	23.92%
	Executives	29	2.72%
	Entrepreneur	27	2.53%
Socioprofessional category	Lower-level white-collar workers	539	50.56%
	Intermediate professions	230	21.58%
	Executives, higher intellectual professions...	162	15.20%
	Blue-collar workers	94	8.82%
	Craftspeople, shopkeepers, and business owners	35	3.28%
	Farmers	6	0.56%

		Counts	Percentage
Sector	Other	333	31.24%
	Education, health, and social action	220	20.64%
	Trade and repair	125	11.73%
	Industry	100	9.38%
	Transport and storage	48	4.50%
	Financial and insurance activities	48	4.50%
	Accommodation and catering	47	4.41%
	Household services	45	4.22%
	Information and communication	39	3.66%
	Construction	28	2.63%
	Business support	21	1.97%
	Real estate activities	12	1.13%