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Are People Mindful in Different Ways? Disentangling the Quantity and Quality of Mindfulness in Latent Profiles and Exploring their Links to Mental Health and Life Effectiveness

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Abstract: We sought to disambiguate the quantitative and qualitative components of mindfulness profiles, examine whether including 'nonattachment' as a subcomponent of mindfulness alters the profiles, and evaluate the extent to which the person-centred approach to understanding mindfulness adds predictive power beyond a more parsimonious variable-centred approach. Using data from a nationally representative sample of Americans (N = 7884; 52% female; Age: M = 47.9, SD = 16), we utilized bifactor exploratory structural equation modelling and latent profile analysis to separate the level and shape of previously identified profiles of mindfulness (Pearson, Lawless, Brown, & Bravo, 2015). Consistent with past research, we identified a judgmentally observing profile and a non-judgmentally aware group, but inconsistent with past research, we did not find profiles that showed high or low levels on all specific aspects of mindfulness. Adding nonattachment did not alter the shape of the profiles. Profile membership was meaningfully related to demographic variables. In models testing the distinctive predictive utility of the profiles, the judgmentally observing profile, compared to the other profiles, showed the highest levels of mental ill-health, but also the highest levels of life satisfaction and effectiveness. We discuss the implications of our study for clinical interventions and understanding the varieties of mindfulness. Copyright © 2017 European Association of Personality Psychology

Key words: mindfulness; nonattachment; latent profile analysis; mixture models; person-centred analysis

Researchers have argued that mindfulness consists of multiple dimensions that tend to 'converge,' that is, be consistently high or low within persons (Baer, Smith, Hopkins, Krietemeyer, & Toney, 2006; Sahdra, Ciarrochi, & Parker, 2016a). These dimensions include observing, describing, acting with awareness, non-judging, non-reactivity, and nonattachment. The assumption of convergence comes largely from variable-centred research, which typically employs factor analysis. However, recent person-centred research has identified subsets of people that are 'divergent,' that is, high in some aspects of mindfulness but low in others (Bravo, Boothe, & Pearson, 2016; Pearson et al., 2015). Specifically, recent studies have identified two divergent profiles, a *non-judgmentally aware* group (low on observing, but high on non-judging and acting with awareness) and a *judgmentally observing* group (high on observing, but low on non-judging and acting with awareness). These studies also identified two convergent profiles, characterized by high scores on all mindfulness facets and moderately low scores on all facets.

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These four profiles were identified based on a statistical method that employed the standardized scores of the five subscales of the Five Facets of Mindfulness Questionnaire (FFMQ; Baer et al., 2006) as indicators in mixture models. One limitation of this approach is that it conflates the 'level' and 'shape' effects in profiles. Broadly speaking, the level effect refers to the quantitative, and the shape effect to the qualitative aspects of the latent profiles. More precisely, the level effect represents the tendency for a person to be high, medium, or low across all mindfulness factors, and the shape effect represents the tendency for a person to have a specific pattern of high, medium, or low levels of the factors. In the previously identified four profiles of mindfulness (Bravo et al., 2016; Pearson et al., 2015), there is no indicator of the global level of the overarching mindfulness construct. Therefore, it becomes difficult to separate the extent to which people generally report high mindfulness across all dimensions (the level effect) from the extent that they are relatively more mindful on some dimensions than others (the shape effect) (Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016b; Morin & Marsh, 2015). Put differently, despite the presence of *high mindfulness* and *low mindfulness* profiles in past research, we cannot be sure whether the differences between the four profiles are due to differences in the global level of mindfulness or the configuration of

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specific aspects of mindfulness, and we cannot be confident that profile membership adds value to the prediction of relevant outcomes above and beyond a variable-centred approach. In short, it remains to be seen whether or not mindfulness profiles add to our knowledge of mindfulness beyond the additive value of the components themselves.

This leads us to our **Research Question 1:** Would the four mindfulness profiles identified in previous research—*non-judgmentally aware, low mindfulness, high mindfulness, and judgmentally observing*—emerge in our sample when we disentangle the level and shape effects in the profiles? To separate the level and shape effects, we utilize a bifactor exploratory structural equation model or B-ESEM (Morin, Arens, & Marsh, 2016a), in which each item is loaded mainly onto two orthogonal factors, a global mindfulness factor and a domain-specific factor, and cross-loadings across items are constrained to be as close to zero as possible. The global factor captures the common underlying construct across all items, and the specific domain factors capture the remaining variance unexplained by the global factor. A profile analysis including both the global and the specific factors from a bifactor model therefore separates the overall level effects from the shapes of the profiles. This approach offers a powerful method for characterizing the variable-centred measurement model of a multidimensional measure such as the FFMQ prior to subjecting the factor scores to a latent profile analysis.

Research on mindfulness profiles so far has focused on the five-factor model of mindfulness. However, prior theorizing (Sahdra & Shaver, 2013; Thera, 1994) and recent empirical research (Sahdra, Ciarrochi, & Parker, 2016a) suggest that there may be an important sixth dimension of mindfulness, termed 'nonattachment.' Whereas the FFMQ measures, among other things, non-reactivity to negative states, it does not measure a 'letting go' of positive states, or nonattachment (Sahdra, Ciarrochi, & Parker, 2016a; Sahdra & Shaver, 2013; Sahdra, Shaver, & Brown, 2010). Non-reactivity involves the ability to experience negative thoughts, images, and situations, without immediately reacting to them. In contrast, nonattachment involves the ability to let go of positive experiences and unrealistic ideas and hopes about life, for instance, that life can be problem-free and perfect (Sahdra, Ciarrochi, Parker, Marshall, & Heaven, 2015; Sahdra et al., 2010). Nonattachment has been shown to load strongly on a global mindfulness factor, to moderately relate to mindfulness factors, especially non-reactivity, but also to show discriminant validity by predicting satisfaction with life and life effectiveness even after controlling for all five mindfulness factors (Sahdra, Ciarrochi, & Parker, 2016a). Based on this evidence, Sahdra, Ciarrochi, and Parker (2016a) argued that nonattachment belongs to the family of mindfulness constructs and adds value to the five facets of mindfulness. Given that nonattachment is an important contributor in defining the global factor of mindfulness, it could help clarify the level and shape effects in latent profiles of mindfulness. This leads to **Research Question 2:** Does the addition of nonattachment to the five factors of mindfulness lead us to identify profiles that differ from those that have been identified in the past?

Person-centred approaches have been argued to add value to variable-centred approaches by focusing on the mindfulness configurations that naturally occur in the population and identifying how particular combinations of mindfulness link to outcomes (Pearson et al., 2015). In other words, the configural 'whole' is believed to be greater than the sum of its parts. For example, it may be that the mindfulness facet of observing is linked to positive outcomes when it is paired with high levels of the mindfulness facet non-judgment, but to negative outcomes when linked to low levels of non-judgment. This is possible in theory as some samples do show a negative correlation between observing and non-judging, particularly in non-meditating participants (Baer et al., 2006). Whilst it is assumed that a person-centred approach adds predictive value over a variable-centred approach to mindfulness, this assumption has not been explicitly tested in past research.

This leads us to **Research Question 3**: Do mindfulness profiles predict variance in mental health and functioning, even after we control for the six mindfulness variables? Controlling for the scale scores while examining the link between profile membership and an outcome provides the most compelling test for whether a person-centred approach is useful in predicting relevant outcomes above and beyond what we can learn from a purely variable-centred approach. If the grouping variable based on the person-centred analysis fails to predict outcomes in models that include scale scores as covariates, then we would argue that the person-centred approach should be abandoned in favor of a parsimonious variable-centred approach.

CURRENT STUDY

We collected data from a large representative sample of Americans and conducted four sets of latent profile analyses (LPA) in an effort to replicate past work and then extend that work by evaluating our three research questions. The first set included an LPA based on the five standardized scores of the FFMQ as indicators in mixture models. The goal of these analyses was to replicate the four mindfulness profiles identified by Bravo et al. (2016) and Pearson et al. (2015). The second set of LPA models employed the factor scores from a bifactor exploratory structural equation model (B-ESEM) of FFMQ as indicators. The goal of this second set of LPA models was to test whether the configurations of the four profiles from the first set of models still emerge once we account for the global factor (Research Question 1). The third set of LPA used the standardized scores of the five subscales of the FFMQ and the sixth score of nonattachment as indicators in mixture models. The goal of these models was to test whether the original 4-profile solution will emerge in a model with nonattachment added to the five facets of the FFMQ (Research Question 2). The final set of LPAs used factor scores from a B-ESEM of the five aspects of FFMQ and the sixth factor of 7-item Nonattachment Scale (NAS-7) assessed nonattachment. The aim of these models was to examine the configuration of a 4-profile solution while separating the level and shape effects

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in a model including nonattachment (Research Questions 1 and 2). Finally, we tested the differences between profiles on relevant outcomes with and without controlling for the scale scores (Research Question 3).

METHOD

Participants and design

We utilized a professional survey company to administer an anonymous survey to a nationally representative American sample (N = 7884; 52% female; Age: M = 47.9, SD = 16). Participants completed the survey online in exchange for points, which they could redeem for merchandize (directly from the company). We collected the following demographic information. Regarding ethnicity background: 7.3% reported African American, 5.6% Hispanic, 8.5% European, 43% European American, 3.4% Asian American, 4.1% Native American, 0.4% Indian subcontinent, 2.6% mixed, multi-racial, and 25% other ethnicities. Participants reported a wide range of educational status: 1.6% had some high school or less, 17.4% had a high school diploma or equivalent, 29.6% had some college education, 28.6% had completed a college diploma, 6.8% had some graduate/professional school training, and 16% reported holding a graduate/professional degree. They varied in socioeconomic status as well, with household income ranging from '$10 000 or less' to 'more than $130 000' (the median category was '$50 001 to $60 000'). Regarding the civil status: 19.7% were single, 0.6% reported dating a number of people, 3.9% dating one person, 53.5% were married, 9.6% were divorced, 5.9% were widowed, 58% were cohabiting (living with a partner as a couple, but not married), and 1.1% were engaged. We also asked participants about their meditation practice: 82% were non-meditators, 11% meditated less than 2 h per week, 4% meditated 2–4 h per week, and 3% meditated more than 4 h per week. The remainder of the survey utilized a planned missing data design, also known as matrix sampling (Graham, Taylor, Olchowski, & Cumsille, 2006; Schafer, 1997), to keep the burden on participants to a minimum. Each participant received a random sample of 60 items from a large battery of 300 items. Each item consisted of responses from at least 21% of the sample (1655 respondents). This sample has been analysed before on a highly related but different topic (Sahdra, Ciarrochi, & Parker, 2016a). (A copy of the data and example analysis scripts can be obtained by contacting the first author of the study.) The current study focused on the following measures:

Measures

Mindfulness

We used a previously validated 20-item Five Facet Mindfulness Questionnaire (Tran, Gluck, & Nader, 2013). Tran et al. (2013) have shown this short form of the FFMQ to have good psychometric properties in student and community samples. Sahdra, Ciarrochi, and Parker (2016a) also showed this measure to have acceptable psychometric properties among community adults. Participants rated their responses to 20 items using a scale from 1 (Never or very rarely true) to 5 (Very often or always true). Example items of the five subscales are as follows: *observing* (e.g. 'I pay attention to sensations, such as the wind in my hair or sun on my face'; α = .77), *describing* (e.g. 'My natural tendency is to put my experiences into words'; α = .76), *acting with awareness* (e.g. 'When I do things, my mind wanders off and I'm easily distracted' (reverse scored); α = .76), *non-judging* of inner experiences (e.g. 'I think some of my emotions are bad or inappropriate and I shouldn't feel them' (reverse scored); α = .79), and *non-reactivity* to inner experiences (e.g. 'When I have distressing thoughts or images, I feel calm soon after'; α = .77).

Nonattachment

The NAS-7 has recently been validated in independent student and community samples of Australians and Americans (Elphinstone, Sahdra, & Ciarrochi, 2015; Sahdra, Ciarrochi, & Parker, 2016a; Sahdra et al., 2015). Participants rated their responses to seven items using a scale from 1 (Disagree Strongly) to 6 (Agree Strongly). Sample items include: 'I can enjoy pleasant experiences without needing them to last forever,' 'I do not get "hung up" on wanting an "ideal" or "perfect" life' (α = .83).

Mental health

We employed the General Health Questionnaire (GHQ, α = .70 in our sample) which is a highly used, reliable, and valid measure of personal mental health (Goldberg, 1978; Goldberg, McDowell, & Newell, 1996). Participants were provided with the sentence stem, 'Have you recently…' followed by 12 response items including, 'been feeling unhappy or depressed,' 'felt you couldn't overcome your difficulties,' 'been able to face up to your problems.' Responses were on a 4-point scale, with labels such as 'Not at all' to 'Much more than usual.' Higher scores indicated greater psychological distress.

Satisfaction with life

We used a well-established measure (Diener, Emmons, Larsen, & Griffin, 1985), in which participants rated their responses to 5 items using a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Example items include: 'In most ways my life is close to my ideal,' and 'I am satisfied with my life.' The measure showed satisfactory internal consistency (α = .85).

Life effectiveness

The 24-item Life Effectiveness Questionnaire (LEQ) measures people's capacity to adapt and thrive in daily life tasks (Neill, Marsh, & Richards, 2003; Purdie, Neill, & Richards, 2002). Participants rated their responses to 24 items using a scale from 1 (False—Unlike me) to 8 (True—Like me). Example items included 'I manage the way I use my time well,' 'I am successful in social situations,' 'I try to do the best that I possibly can,' 'I change my thinking or opinions easily if there is a better idea,' 'I am a good

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leader when a task needs to be done,' 'I can stay calm in stressful situations,' 'I like to be active 'get into it' person,' and 'When I apply myself to something I am confident I will succeed.' All the items of the measure showed high internal consistency (α = .91).

Multiple imputation procedure

Because we utilized a missing-data-by-design procedure, the data were missing completely at random or MCAR (Enders, 2010). This allowed us to utilize a multiple imputation procedure to produce unbiased estimates (Little & Rubin, 1987). We generated 25 imputations using the package, Amelia II (Honaker, King, & Blackwell, 2011) in the statistical software R (R_Core_Team, 2015). Additional details of the procedure are reported elsewhere (Sahdra, Ciarrochi, & Parker, 2016a; Sahdra, Ciarrochi, Parker, & Scrucca, 2016b). Amelia II imputes missing data using a bootstrapped expectation–maximization (EMB) procedure. It uses the expectation–maximization (EM) algorithm on multiple bootstrapped samples of the original incomplete data to draw values of the complete-data parameters, which are then used to draw imputed values replacing the missing values. We employed the diagnostics functions of Amelia II to examine the imputed datasets. The EM convergence was normal, and EM chain lengths of all 25 imputed datasets were reasonably short and consistent in length. The compare-density function of Amelia II showed that the distribution of imputed values was comparable to the distribution of observed values. The overimpute function confirmed that the observed data tended to fall within the region where it would have been imputed had it been missing instead of observed. We also examined relative efficiency of imputed datasets by comparing the mean of each scale to a theoretical estimate computed using an infinite number of imputations. Relative efficiency estimates close to 1 indicate that the imputed data matches the theoretical ideal (Rubin, 1987; Schafer, 1999). In our case, the relative efficiency estimates of scale means were consistently above .99. In short, all our diagnostic tests indicated that our imputation model was robust.

Statistical analysis approach

We conducted bifactor exploratory structural equation models or B-ESEM (Morin, Arens, & Marsh, 2016a) in order to separate the level and shape effects in latent profiles of mindfulness. We note that good-fitting alternate models of the 20-item FFMQ and the NAS-7 have been published before: in particular, a single higher-order CFA of FFMQ and NAS-7 items (Sahdra, Ciarrochi, & Parker, 2016a), and a two higher-order factors ESEM of the 20-item FFMQ (Tran et al., 2013). (See Supporting Information S1 for comparison of the bifactor models using two higher order global factors with the models using single global factors.) The key difference between a higher-order factor model and a bifactor model is that the higher-order model assumes that the higher-order factor has an influence on the items only via the lower order factors. A bifactor model makes no such assumption, that is, the higher-order factor has both direct and indirect effects on the items in a bifactor model, as demonstrated by the following set of equations:

In a standard CFA, an observed item y is given by the equation:

$$y = \nu + \lambda_1 \times F1 + \epsilon \tag{1}$$

A higher-order model does not change this equation because the higher-order factor G has an effect on y only via its effect on $F1$ where:

$$F1 = \alpha + \beta_2 \times G + \zeta \tag{2}$$

The only way to get the effect of G on y is via the Schmid Leiman transformation equation:

$$\lambda_1 \times \beta_2 \tag{3}$$

In a bifactor model, the standard CFA equation is modified as follows:

$$y = \nu + \lambda_1 \times F1 + \lambda_2 \times G + \epsilon \tag{4}$$

Note that G has a direct effect on y rather than just an indirect effect via $F1$. Also note that when $\lambda_1 = 0$, Equation (1) is equivalent to Equation (4), and thus a higher-order model can be considered as nested within the more general bifactor model.

Factor mixture analysis, which uses a higher-order factor from a hierarchical model, has been proposed as one possible way of separating the level and shape effects in latent profiles (Morin & Marsh, 2015). The issue with this approach, however, is that the higher-order factor score is psychometrically redundant with the first-order factor scores, which are meant to be the indicators in subsequent latent profile analysis. This issue can be resolved by using a bifactor model instead (Morin, Boudrias, et al., 2016b). In the B-ESEM that we ran, each item was loaded onto two orthogonal factors, a global mindfulness factor and a domain-specific factor. Cross-loadings across items were allowed, but constrained to be as close to zero as possible. The global factor of B-ESEM thus represents the overall level of mindfulness, and the specific factors represent deviations of the individual factors from an overall level of mindfulness that is apparent across all facets. To derive latent profiles of mindfulness, we used the factor scores from B-ESEM as indicators in LPA models.

Because the B-ESEM separates a global factor of the underlying construct common across all items from the specific factors, LPA based on B-ESEM factor scores allowed us to account for the global mindfulness level effects while examining the shape of the levels of the specific facets of mindfulness. We also ran LPA models using the standardized scale scores to see how the results compared to the LPA models using the B-ESEM factor scores. In both cases, the indicators of

DOI: 10.1002/per

LPA—either standardized scale scores or factor scores—were calculated using the 25 imputed datasets, so there were no missing data in any of our LPA models. To avoid local maxima, all LPA were conducted using 5000 random sets of start values, 2000 iterations, and retained the 200 best solutions for final stage optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000).

Regarding selecting the number of profiles in LPA, there are three crucial factors guiding the decision process: the substantive meaning of the profiles, theoretical conformity, and statistical adequacy (e.g. absence of negative variance estimates) of the solution (Bauer & Curran, 2003; Marsh, Lüdtke, Trautwein, & Morin, 2009; Muthén, 2003). Several statistical indices can support the selection of number of profiles (McLachlan & Peel, 2000): (i) The Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendell, and Rubin's (2001) LRTs (LMR/aLMR, as these tests typically yield the same conclusions, we only report the aLMR), and (vi) the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC, and ABIC suggests a better-fitting model. A significant p value for the aLMR and BLRT can be used to support the model with one fewer latent profile. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are effective and that when the indicators fail to retain the optimal model, the ABIC and BLRT tend to overestimate the number of classes, whereas the BIC, CAIC, and aLMR tend to underestimate it (Nylund, Asparouhov, & Muthen, 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Yang, 2006). However, these tests remain heavily influenced by sample size (Marsh et al., 2009), so that with sufficiently large sample sizes, such as in our study, they may suggest the addition of profiles without ever reaching a minimum. In such cases, theoretical reasons and prior research, if available, are especially important to the decision process. 'Elbow plots' of the information criteria can sometimes help in the decision process—the optimal number of profiles usually falls at the point of a relative plateau in such graphs (Morin, Boudrias, et al., 2016b)—but they are not always helpful, especially in very large sample sizes, where increasing number of profiles is often associated with increasingly better fit indices without reaching an easily identifiable plateau. Another statistical index, the entropy, indicates the precision with which the cases are classified into the various profiles. The entropy should not be used in isolation to determine the optimal number of profiles (Lubke & Muthen, 2007), but provides a useful summary of the classification accuracy, varying from 0 to 1, with higher values indicating more accuracy. The entropy around .80 is considered high (Clark & Muthén, 2009).

While considering the statistical indices, it is important to note that it is technically impossible to distinguish a k-profile LPA solution from a $k - 1$ factor model on the sole basis of statistical information as both models are empirically equivalent in most respects (Cudek & Henly, 2003; Steinley & McDonald, 2007) and spurious latent profiles often emerge to compensate for violations of the model's distributional assumptions, which are impossible to systematically assess in practice (Bauer & Curran, 2003). Therefore, guided by theoretical considerations and prior research (Baer et al., 2006; Pearson et al., 2015; Sahdra, Ciarrochi, & Parker, 2016a), we took a more confirmatory approach by favouring a 4-profile solution in our study as long as it was statistically adequate considering all available information.

We ran four sets of LPAs. First, using a traditional LPA method, we used standardized scale scores of the FFMQ as indicators in LPA and selected a 4-class solution, Model A, which allowed us to replicate the shape of the four mindfulness profiles reported by Pearson et al. (2015) and Bravo et al. (2016). To extend prior research, we conducted three additional sets of LPAs. Our Model B was a 4-class solution from our second set of LPAs, which employed as indicators the factor scores from a B-ESEM of the FFMQ. We then added nonattachment items to broaden the scope of mindfulness measurement in our models based on recent research (Sahdra, Ciarrochi, & Parker, 2016a). Our Model C was a 4-class LPA solution based on the standardized scores of the FFMQ and NAS-7. Finally, our Model D was a 4-class LPA solution based on the factor scores of a B-ESEM of the FFMQ and NAS-7. In each of the four sets of models, the 4-class solution was statistically sound given all available information.

However, while selecting the 4-profile solution in each set, we did examine the shapes of the three-profile and five-profile solutions to check whether these models adjacent to our selected 4-profile solutions provided better clarity to our results. They did not. The three-profile solutions conflated two profiles that were qualitatively distinct in the 4-profile solutions. The five-profile solutions simply added another group, which was split from one of the groups in the 4-profile solutions that had the same shape and level, so was not qualitatively distinct from it. As is often the case with latent profile analysis using large samples, increasing the number of profiles continues to improve the fit statistics, but often by over-fitting and creating additional groups that do not necessarily differ qualitatively (in shape) from some of the other groups in the same solution. We were able to avoid this pitfall by relying on the relevant prior theory and research in this area (Baer et al., 2006; Pearson et al., 2015; Sahdra, Ciarrochi, & Parker, 2016a).

All the B-ESEM and LPA models were conducted in M*plus*, Version 7.4 (Muthén & Muthén, 2015). The B-ESEM employed WLSMV estimation and the LPAs employed robust maximum likelihood estimation. All other analyses reported below were conducted in R (R_Core_Team, 2015) using the following packages: arm (Gelman & Su, 2015), ggplot2 (Wickham, 2009), gridExtra (Baptiste, 2016), reshape2 (Wickham, 2007), aod (Lesnoff & Lancelot, 2012), car (Fox & Weisberg, 2010), MASS (Venables & Ripley, 2013), miceadds (Robitzsch, Grund, & Henke, 2014), mitools (Lumley, 2014), MplusAutomation (Hallquist & Wiley, 2013), nnet (Venables & Ripley, 2013), and psych (Revelle, 2015).

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RESULTS

Zero-order correlations

Table 1 reports the means, standard deviations, and inter-correlations between the study variables. The various aspects of mindfulness and nonattachment were generally interrelated, suggesting a common manifold. As in past research, the only exception to the positive manifold was the observing factor, which did not correlate with acting with awareness or non-judgment. The mindfulness variables were related in theoretically expected ways to the indices of mental health and effective functioning, showing negative correlations with mental ill-health, and positive correlations with satisfaction with life and life effectiveness.

Latent profile analyses of the Five Facets of Mindfulness Questionnaire

We next investigated the extent to which separating the level and shape effects (using B-ESEM) would yield similar or different mindfulness profiles than the ones reported in past approaches (Research Question 1). We attempted to replicate the 4-class LPA solution reported by Pearson et al. (2015) and Bravo et al. (2016) using the standardized scores of the five subscales of the FFMQ. We then conducted a B-ESEM of FFMQ and used the factor scores from that model as indicators in LPA. The fit indices of the B-ESEM model were as follows: $\chi^2(85) = 2643.89$, $p < .001$, CFI = .97, TLI = .93, RMSEA = .06 [90% CI: 0.05 0.06]. The model fit the data well according to the commonly accepted fit criteria of CFI/TLI ≥ .90 and RMSEA ≤ .06 (Bentler, 1990; Hu & Bentler, 1999; Kenny, Kaniskan, & McCoach, 2014). (See Table S1 in Supporting Information S2 for the factor loadings of the B-ESEM.) In addition to controlling for measurement error, the B-ESEM clarifies the measurement model by separating the global component of mindfulness from the specific aspects. Table 2 reports the results from the two sets of LPAs. The first set of models (the top panel of Table 2) used the standardized scale scores as LPA indicators, and the second set of models used the B-ESEM factor scores as indicators of LPA.

The fit indices reported in Table 2 and the 'elbow plots' (see Supporting Information S3) seemed to suggest better fitting models with increasing number of profiles. This is a common issue in profile analysis, and model selection should be based on all available information, including relevant past research. Fortunately, we had strong a priori reasons for selecting the 4-profile solution based on prior theory and research on mindfulness profiles (Pearson et al., 2015). The examination of the 4-profile solution and of the adjacent three- and five-profile solutions showed that all solutions were statistically adequate (e.g. there were no convergence issues or negative variances). Further, adding a fourth profile resulted in the addition of a well-defined qualitatively distinct and theoretically meaningful profile to the solution, whereas adding a fifth profile resulted in the arbitrary division of one of the existing profile into two profiles differing only quantitatively from one another. Therefore, Model A (as highlighted in Table 2 and depicted in Figure 1) was a statistically sound choice in our first set of LPA models and seemed to be consistent with the previously reported profiles by Pearson et al. (2015) and Bravo et al. (2016).

One of the main goals of the study was to test whether the configuration of the four mindfulness profiles from previous research still emerges once we control for the global factor (Research Question 1), so the 4-profile solution of Model B (as highlighted in Table 2) from our second set of LPAs was selected to compare the shape of the profiles observed in Model A. Figure 1 depicts the patterns of means (thick white lines) and individual scores (thin black lines) of the indicators in Models A and B. Note that we chose to plot all of the data, not just the means (as is the common practice in mixture model papers) to facilitate visualization of the dispersion of individuals' scores around the mean in the profile structure. (Readers interested in comparing the means and standard errors of the mindfulness facets in the four profiles of our Model A to those reported by Bravo et al. (2016) and Pearson et al. (2015) can find those details in Section S4 of Supporting Information).

As shown in the left panel of Figure 1, Model A exactly replicated the profile shapes previously reported by Pearson et al. (2015) and Bravo et al. (2016). However, in answer

Table 1. Zero-order correlations, means, and standard deviations (SD) of all variables

	MD	OB	DS	AW	NJ	NR	NS	GHQ	SWL	LE
OB	0.51									
DS	0.73	0.3								
AW	0.71	0.03 ^{ns}	0.4							
NJ	0.69	−0.01^{ns}	0.37	0.59						
NR	0.59	0.4	0.34	0.15	0.14					
NS	0.63	0.42	0.39	0.31	0.32	0.64				
GHQ	−0.51	−0.04 ^{ns}	−0.35	−0.5	−0.5	−0.19	−0.35			
SWL	0.37	0.18	0.27	0.15	0.19	0.45	0.52	−0.33		
LE	0.63	0.48	0.49	0.19	0.12	0.59	0.7	−0.28	0.54	
Mean	3.48	3.72	3.36	3.46	3.42	3.4	4.64	2.18	3.26	5.97
SD	0.47	0.63	0.59	0.73	0.77	0.6	0.76	0.37	0.79	1.05

Note. MD: Overall score of mindfulness averaging across all items of the 20-item FFMQ; OB: Observing; DS: Describing; AW: Acting with awareness; NJ: Non-judging; NR: Non-reactivity; NS: Nonattachment; GHQ: General Health Questionnaire (measuring mental ill-health); SWL: Satisfaction with life; LE: Life effectiveness. All correlations were significant ($p < .01$) unless *note*d as *ns*.

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Table 2. Results from two sets of latent profile analysis (LPA) models using the standardized scale scores of FFMQ as indicators (top panel) and the factor scores of a B-ESEM of FFMQ as indicators (bottom panel)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT	Sm. n	
Models using the five standardized scale scores of FFMQ as indicators of LPA												
1 Profile	−55 932.057	10	1.0700	111 884.114	111 884.142	111 953.84	111 922.062	—	—	—	7884	
2 Profiles	−52 280.874	21	1.2109	104 603.749	104 603.867	104 750.173	104 683.439	0.746	≤.001	≤.001	3267	
3 Profiles	−50 650.812	32	1.3231	101 365.623	101 365.892	101 588.746	101 487.057	0.747	≤.001	≤.001	3171	
4 Profiles	−49 809.504	43	1.2001	99 705.008	99 705.491	100 004.83	99 868.184	0.817	≤.001	≤.001	260	Model A
5 Profiles	−49 086.199	54	1.3015	98 280.398	98 281.157	98 656.917	98 485.316	0.765	≤.001	≤.001	332	
6 Profiles	−48 531.509	65	1.3223	97 193.018	97 194.115	97 646.236	97 439.679	0.779	≤.001	≤.001	131	
7 Profiles	−48 214.264	76	1.3457	96 580.529	96 582.028	97 110.446	96 868.933	0.771	.001	≤.001	132	
8 Profiles	−47 913.093	87	1.3027	96 000.186	96 002.15	96 606.802	96 330.333	0.758	≤.001	≤.001	135	
Models using the six factor scores from a B-ESEM of FFMQ as indicators of LPA												
1 Profile	−47 856.278	12	1.1110	95 736.556	95 736.596	95 820.227	95 782.093	—	—	—	7884	
2 Profiles	−43 676.362	25	1.3098	87 402.725	87 402.890	87 577.040	87 497.595	0.748	≤.001	≤.001	3468	
3 Profiles	−41 871.227	38	1.2869	83 818.455	83 818.833	84 083.413	83 962.657	0.768	≤.001	≤.001	898	
4 Profiles	−40 537.007	51	1.5170	81 176.015	81 176.692	81 531.617	81 369.549	0.809	≤.001	≤.001	624	Model B
5 Profiles	−39 352.908	64	1.3106	78 833.816	78 834.880	79 280.061	79 076.682	0.798	≤.001	≤.001	507	
6 Profiles	−38 619.499	77	1.3018	77 392.997	77 394.536	77 929.887	77 685.196	0.791	≤.001	≤.001	169	
7 Profiles	−38 203.28	90	1.3776	76 586.561	76 588.663	77 214.094	76 928.092	0.789	.004	≤.001	134	
8 Profiles	−37 852.558	103	1.3321	75 911.116	75 913.870	76 629.292	76 301.979	0.798	≤.001	≤.001	130	

Note. B-ESEM: Bifactor Exploratory Structural Equation Modelling; FFMQ: Five Factor Mindfulness Questionnaire (the short form of 20 items); LL: model loglikelihood; #fp: number of free parameters; scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: sample-size adjusted BIC; aLMR: adjusted Lo–Mendel–Rubin likelihood ratio test; BLRT: bootstrapped likelihood ratio test; Sm n: the sample size of the smallest profile. Models A and B highlighted in grey were selected a-priori based on previous research by Pearson et al. (2015) and Bravo et al. (2016).

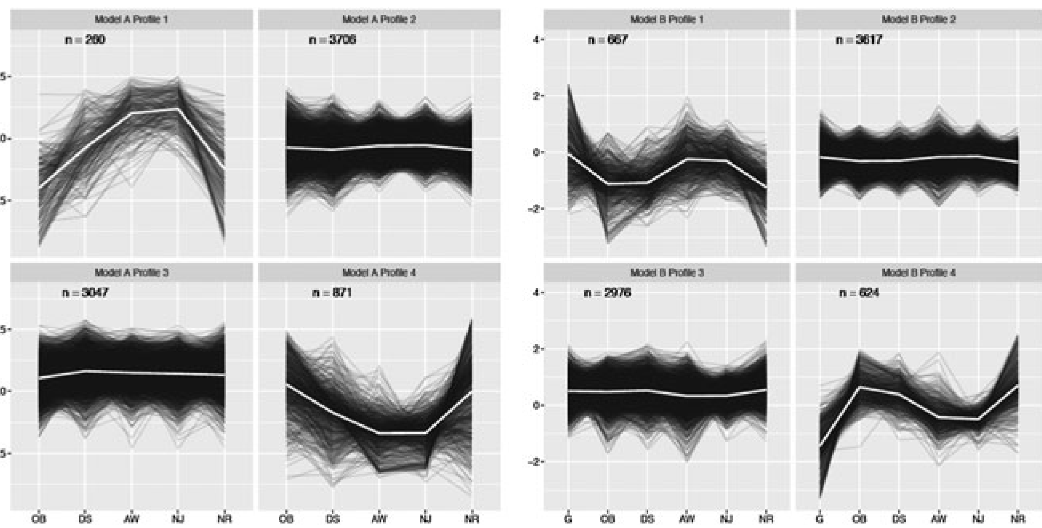

Figure 1. The pattern of means (thick white lines) and individual scores (thin black lines) of the five facets of mindfulness in the four latent classes derived using the standardized scale scores of FFMQ (Model A) and using factor scores from a B-ESEM of FFMQ (Model B). G: Global mindfulness factor; OB: Observing; DS: Describing; AW: Acting with awareness; NJ: Non-judging; NR: Non-reactivity.

to our Research Question 1, as shown in the right panel of Figure 2, we obtained only partial replication of the shapes of previously observed four profiles of mindfulness in our Model B that included the global factor of the FFMQ. The shape of the Profile 4 of Model A, the *judgmentally observing* group, was almost exactly replicated in the shape of Profile 4 in Model B. However, Profile 1 in Model A, the *non-judgmentally aware* group, was not replicated in Model B. Profile 1 in Model B showed below average scores on observing, describing and non-reactivity, but close to average scores on non-judgment and acting with awareness. Thus, Profile 1 in Model B was importantly different from Profile 1 in Model A, which showed above average scores on non-judgment and acting with awareness. These results could either mean (i) that people in the general population do not correspond to the *non-judgmentally aware* profile or (ii) that some unknown percentage of people do correspond to this profile but the indicators used to measure this profile in Model B fail to capture that. If this profile fails to emerge once we add more information in the model (i.e. nonattachment) to better represent the global factor of mindfulness, as we will do below, that would cast further

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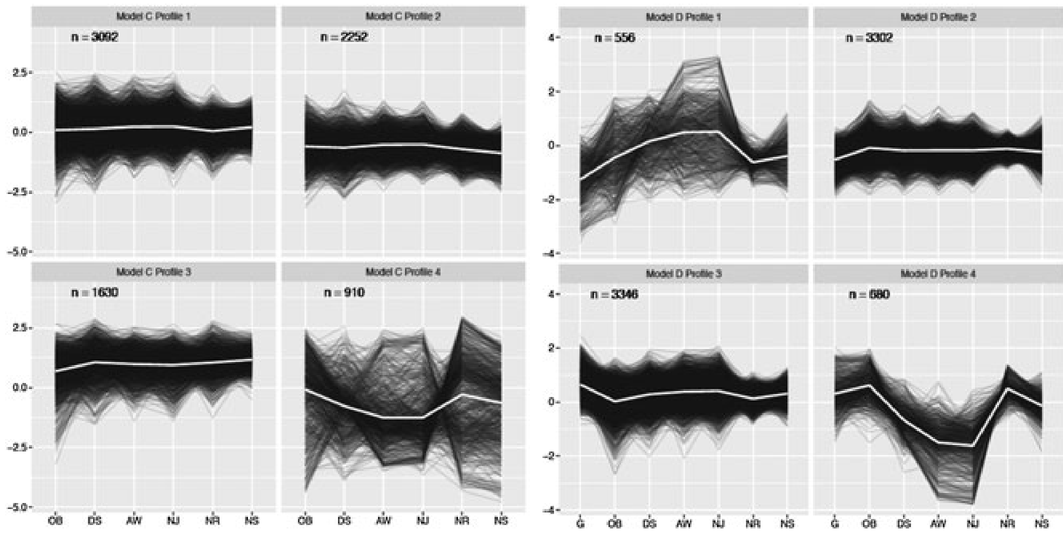

Figure 2. The pattern of means (think white lines) and individual scores (thin black lines) of the five facets of mindfulness and nonattachment in the four latent classes derived using the standardized scale scores of FFMQ and NAS-7 (Model C) and using factor scores from a B-ESEM of FFMQ and NAS-7 (Model D). G: Global mindfulness factor; OB: Observing; DS: Describing; AW: Acting with awareness; NJ: Non-judging; NR: Non-reactivity; NS: Nonattachment. Model D is the final selected model. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*.

doubt as to whether subpopulations can be meaningfully characterized by a *non-judgmentally aware* profile.

Latent profile analyses of the Five Facets of Mindfulness Questionnaire and 7-item Nonattachment Scale

We investigated the extent to which adding nonattachment to the five mindfulness factors altered the 4-profile solutions observed in Models A and B (Research Question 2). We conducted two sets of LPA models in which nonattachment was added to the mix of the five factors of mindfulness (see Table 3 for the details of the results). The first set of models included the standardized scores of the five facets of FFMQ and NAS-7 as indicators of LPA. The 4-profile solution from these models is labelled Model C in Table 3. As shown in Figure 2, the shapes of Profiles 2 to 4 of Model C were comparable to the shapes of the corresponding profiles in

Table 3. Results from two sets of latent profile analysis (LPA) models using the standardized scale scores of FFMQ and NAS-7 as indicators (top panel) and the factor scores of a B-ESEM of FFMQ and NAS-7 as indicators (bottom panel)

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT	Sm. n	
Models using the six standardized scale scores of FFMQ and NAS-7 as indicators of LPA												
1 Profile	−67 118.468	12	1.093	134 260.936	134 260.976	134 344.607	134 306.474	—	—	—	7884	
2 Profiles	−61 462.014	25	1.2435	122 974.029	122 974.194	123 148.343	123 068.898	0.803	≤.001	≤.001	3305	
3 Profiles	−59 209.293	38	1.2785	118 494.585	118 494.963	118 759.544	118 638.787	0.806	≤.001	≤.001	897	
4 Profiles	−57 705.428	51	1.2601	115 512.856	115 513.533	115 868.458	115 706.391	0.792	≤.001	≤.001	910	Model C
5 Profiles	−56 440.397	64	1.2662	113 008.795	113 009.859	113 455.040	113 251.661	0.835	≤.001	≤.001	433	
6 Profiles	−55 817.804	77	1.3433	111 789.608	111 791.147	112 326.497	112 081.807	0.842	≤.001	≤.001	134	
7 Profiles	−55 340.890	90	1.4277	110 861.780	110 863.882	111 489.313	111 203.311	0.814	≤.001	≤.001	136	
8 Profiles	−54 907.428	103	1.3807	110 020.856	110 023.610	110 739.033	110 411.719	0.817	≤.001	≤.001	137	
Models using the seven factor scores from a B-ESEM of FFMQ and NAS-7 as indicators of LPA												
1 Profile	−52 995.657	14	1.2060	106 019.315	106 019.368	106 116.931	106 072.442	—	—	—	7884	
2 Profiles	−49 647.334	29	1.3722	99 352.667	99 352.889	99 554.873	99 462.716	0.693	≤.001	≤.001	3853	
3 Profiles	−46 740.148	44	1.3031	93 568.296	93 568.801	93 875.090	93 735.267	0.764	≤.001	≤.001	932	
4 Profiles	−44 995.491	59	1.3045	90 108.982	90 109.887	90 520.365	90 332.875	0.818	≤.001	≤.001	556	Model D
5 Profiles	−43 939.12	74	1.3161	88 026.241	88 027.662	88 542.212	88 307.055	0.825	≤.001	≤.001	157	
6 Profiles	−42 960.852	89	1.3314	86 099.704	86 101.759	86 720.265	86 437.441	0.812	≤.001	≤.001	155	
7 Profiles	−42 264.748	104	1.3988	84 737.496	84 740.304	85 462.646	85 132.155	0.808	≤.001	≤.001	144	
8 Profiles	−41 679.757	119	1.4647	83 597.513	83 601.192	84 427.252	84 049.093	0.810	.223	≤.001	92	

Note. B-ESEM: Bifactor Exploratory Structural Equation Modelling; FFMQ: Five Factor Mindfulness Questionnaire (the short form of 20 items); NAS-7: The 7-item Nonattachment Scale; LL: model loglikelihood; #fp: number of free parameters; scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: sample-size adjusted BIC; aLMR: adjusted Lo–Mendel–Rubin likelihood ratio test; BLRT: bootstrapped likelihood ratio test; Sm n: the sample size of the smallest profile. The models highlighted in grey are selected models. Model C was selected for comparison with Models A and B, which did not have a general factor. Model D was the most parsimonious solution based on all available information.

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Model A. However, Profile 1 of Model A, the *non-judgmentally aware* profile, failed to replicate in Model C.

In the final set of LPAs, we used factor scores from a B-ESEM of FFMQ and NAS-7 together. The B-ESEM model fit the data well ($\chi^2(183) = 5458.94$, $p < .001$, CFI = .95, TLI = .91, RMSEA = .06 [90% CI: 0.05 0.06]). (See Table S2 in Supporting Information S2 for the factor loadings of the B-ESEM.) Table 3 reports the results of this set of LPA models and highlights the final selected 4-profile solution as Model D.

The right panel of Figure 2 depicts the four profiles in Model D. The global factor from the B-ESEM is arguably the strongest indicator of global mindfulness level and should offer the best chance of clarifying the *non-judgmentally aware* Profile 1 that was poorly defined in both Models B and C above. Indeed, it does to some extent. The shape of Model D Profile 1 (the right panel of Figure 2) is similar to the shape of Model A Profile 1 (the left panel of Figure 1). The levels of non-judgment and acting with awareness were about half a standard deviation above the mean in Model D Profile 1, whereas they were a full standard deviation above the mean in Model A Profile 1 (see Supporting Information S4 for means of the indicators in Models A to D). These results lend some support to the notion that a small proportion of individuals (about 7% in Model D) can be characterized as *non-judgmentally aware* group. The shape of Model D Profile 2, *average mindfulness* profile, was relatively flat with average levels of specific aspects of mindfulness. Non-judgment scores were slightly above average in Model D Profile 3, *moderately non-judgmental* profile. The level of the global factor was slightly below the mean in Profile 2 and slightly above the mean in Profile 3 in Model D. Thus, using B-ESEM, we did not find profiles that showed all-high or all-low levels of the specific factors of mindfulness, as identified in previous research using the traditional method of LPA on standardized scale scores (Pearson et al., 2015) and in our own models using the standardized scale scores (Models A and C). Note that an all-high or all-low profile did not emerge even in the five-profile solution, which showed four profiles that were identical in shape to Profiles 1 to 4 of Model D and one extra group qualitatively similar to Profile 4.

Our Models A to D are alternate ‘maps’ of reality. While examining the links of profile membership with the outcome variables, we compared Model A, which was based on the standardized scores of the FFMQ, to our Model D, which was based on the B-ESEM factor scores of the FFMQ and NAS-7. A cross-tabulation of classifications of participants in the four profiles in Model A and D yielded a kappa of 0.64, which indicates a reasonably good agreement (Landis & Koch, 1977) between the two models despite the different underlying models of the structure of mindfulness informing these two LPAs (see S5 in Supporting Information for cross-tabulations of all models).

The shape of Profile 4 in Model D was identical to the shape observed in Profile 4 of all previous Models A to C. Overall, all the LPAs showed that the shape of Profile 4, the *judgmentally observing* group, seemed to be the most robust configuration that consistently emerged in each of the Models A to D. We hasten to add that this was a relatively small group (about 9% of the sample in Model D). Interestingly, Model D Profiles 1 and 4 differed from each other not only in the configuration of the different levels of the six specific indicators of mindfulness (the shape effect) but also in the level of the global indicator of mindfulness (the level effect). The global factor in Profile 1 was about 1 standard deviation below the mean, whereas the global factor level in Profile 4 was very close to the mean. Put differently, Profiles 1 and 4 in Model D were mirror images of each other in all respects except the level of global mindfulness. Thus, in answer to our Research Question 1, the B-ESEM-based LPA Model D successfully disentangled the level and shape effects in the profiles of mindfulness.

Demographic predictors of profile membership

For our final selected Model D, we examined the associations of the demographic predictors of age, gender, and meditation practice with membership in one of the four profiles: *non-judgmentally aware, average mindfulness, moderately non-judgmental,* and *judgmentally observing* profiles. Although we did not have clear a priori hypotheses about demographic predictors (because we did not know whether the previously observed four latent profiles of mindfulness would withstand our statistical tests separating the level and shape effects), meaningful links between demographic predictors and profile membership observed post-hoc would provide preliminary evidence for the construct validity of the profiles. Past research indicates that meditation experience is associated with higher scores on mindfulness (Brown & Ryan, 2003) and nonattachment (Sahdra et al., 2010), so experienced meditators may be especially likely to belong to a profile with an above average level of the global mindfulness factor, relative to any other profile.

We conducted multinomial logistic regression models (with 25 imputed datasets) using age and gender as predictors of profile membership in Model D. Table 4 reports the coefficients, standard errors, and odds ratios, and Figure 3 depicts the predicted probabilities. Males and females were equally likely to belong to Profile 1, the *non-judgmentally aware* group, and there was no age-related variation in probability of belonging to this profile. Younger participants were more likely than older participants to belong to Profile 2, the *average mindfulness* group. Females of all ages had slightly higher probability than males to belong to Profile 3, the *moderately non-judgmental* group, and older people were more likely to belong to this profile than younger participants. Finally, older participants of both genders were less likely than younger ones to belong to Profile 4, the *judgmentally observing* group, but (younger) males were slightly more likely than (younger) females to belong to this profile.

Regarding meditation experience, we asked participants, ‘Do you currently have a meditation practice?’ and provided the following response options: (1) No; (2) Yes, less than 1 hour per week; (3) Yes, 1–2 h per week; (4) Yes, 2–3 h per week; (5) Yes, 3–4 h per week; (6) Yes, 4–5 h per week; and (7) Yes, more than 5 h per week. If participants reported that they meditated, they were further asked, ‘Please describe the

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Table 4. Results of multinomial logistic regression models with age and gender predicting membership in the latent profiles of Model D

	Intercept				Gender (females)				Age			
	Estimate	SE	*p*	OR [95% CI]	Estimate	SE	*p*	OR [95% CI]	Estimate	SE	*p*	OR [95% CI]
Profile 1 as a reference category												
Profile 2	1.69	0.14	<.001	5.42 [5.15 5.69]	−0.25	0.09	0.01	0.78 [0.78 0.96]	0.00	0.001	0.57	1.000 [0.998 1.001]
Profile 3	−0.15	0.15	0.37	0.86 [0.57 1.15]	−0.08	0.09	0.39	0.92 [0.75 1.10]	0.04	0.001	<.001	1.041 [1.039 1.043]
Profile 4	1.47	0.18	<.001	4.35 [4.00 4.70]	−0.87	0.11	<.001	0.42 [0.20 0.63]	−0.02	0.001	<.001	0.980 [0.978 0.982]
Profile 2 as a reference category												
Profile 1	−1.69	0.14	<.001	0.18 [−0.09 0.46]	0.25	0.09	0.01	1.28 [1.11 1.46]	0.00	0.001	0.57	1.000 [0.998 1.001]
Profile 3	−1.84	0.09	<.001	0.16 [−0.02 0.34]	0.16	0.05	<.001	1.17 [1.08 1.27]	0.04	0.001	<.001	1.041 [1.039 1.043]
Profile 4	−0.22	0.14	0.15	0.80 [0.53 1.08]	−0.62	0.09	<.001	0.54 [0.36 0.74]	−0.02	0.001	<.001	0.980 [0.978 0.982]
Profile 3 as a reference category												
Profile 1	0.15	0.15	0.37	1.16 [0.87 1.46]	0.08	0.09	0.39	1.09 [0.91 1.26]	−0.04	0.001	<.001	0.961 [0.959 0.963]
Profile 2	1.84	0.09	<.001	6.30 [6.12 6.47]	−0.16	0.05	<.001	0.85 [0.75 0.95]	−0.04	0.001	<.001	0.961 [0.959 0.963]
Profile 4	1.62	0.14	<.001	5.05 [4.78 5.33]	−0.78	0.09	<.001	0.46 [0.28 0.63]	−0.06	0.001	<.001	0.942 [0.940 0.944]
Profile 4 as a reference category												
Profile 1	−1.47	0.18	<.001	0.23 [−0.12 0.58]	0.87	0.11	<.001	2.39 [2.17 2.60]	0.02	0.001	<.001	1.020 [1.018 1.022]
Profile 2	0.22	0.14	0.15	1.24 [0.97 1.52]	0.62	0.09	<.001	1.86 [1.68 2.04]	0.02	0.001	<.001	1.020 [1.018 1.022]
Profile 3	−1.62	0.14	<.001	0.2 [−0.08 0.47]	0.78	0.09	<.001	2.18 [2.01 2.36]	0.06	0.001	<.001	1.026 [1.060 1.064]

Note. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*. SE: standard error; OR: odds ratio; CI: Confidence Interval.

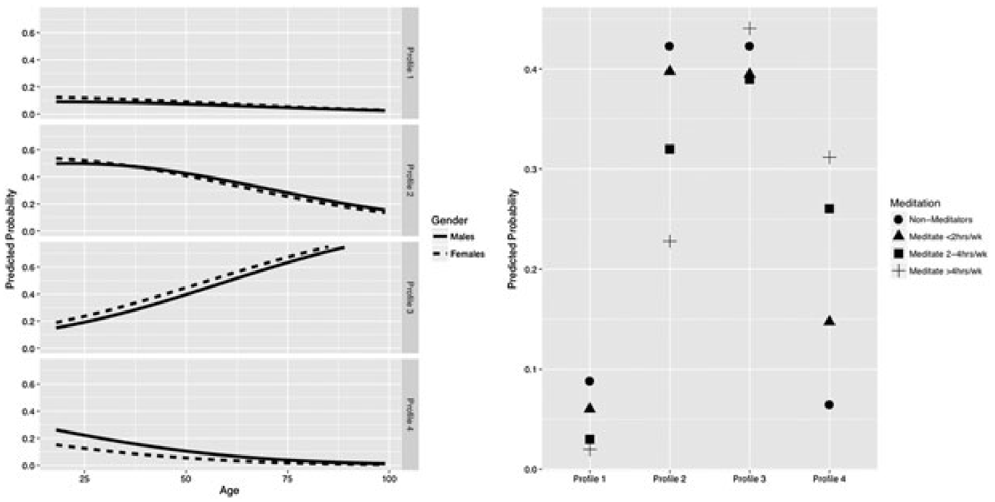

Figure 3. Predicted probability of being a member of one of the four profiles of Model D as a function of age and gender (left panel) and meditation practice (right panel). Profile 1: *Non-judgmentally aware*; Profile 2: *Average mindfulness*; Profile 3: *Moderately non-judgmental*; Profile 4: *Judgmentally observing*.

kind of meditation you practice.' Of the meditators ($n = 1417$), only about half of them ($n = 747$) provided a description of their practice, and typically they wrote a single word (e.g. 'zen,' 'mindfulness,' 'vipassana', 'centering', 'yoga', 'quiet time prayer', 'sit and chant'). Because the kinds of meditation that participants reported were diverse and the sample sizes in the various kinds of meditation were too small for a systematic evaluation of the type of meditation practice in relation to the latent profiles, we focused mainly on the original question about meditation to examine the link between meditation (of any type) and profile membership. Based on those data, we created the following categories of meditation practice: (i) non-meditators; (ii) meditators who practiced less than 2 h per week; (iii) meditators who practiced 2 to 4 h a week; and (iv) meditators who practiced more than 4 h per week. A chi-square test (based on 25 imputed datasets) revealed a non-linear relationship between profile membership and meditation practice: $\chi^2(9, N = 7884) = 305.15$, $p < .001$. Table 5 shows the number of participants (in one of the imputed datasets) in each of the eight cells of the contingency table.

To compute the log odds of membership in the four profiles as a function of meditation practice, we conducted multinomial logistic regression (using 25 imputed datasets) with profile membership regressed on the different categories of meditation practice. Table 6 reports the coefficients, standard errors, and odds ratios from the multinomial logistic regression models for meditation practice, and Figure 3 plots

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Table 5. Number of participants in different meditation categories across the four profiles of Model D

	Non-meditators	Meditate <2 h/week	Meditate 2–4 h/week	Meditate >4 h/week
Profile 1: *Non-judgmentally aware*	560	58	11	5
Profile 2: *Average mindfulness*	2736	323	105	57
Profile 3: *Moderately non-judgmental*	2731	332	130	110
Profile 4: *Judgmentally observing*	440	121	91	74

the predicted probabilities of being in each of the cells. Between-profile predicted probabilities of meditators showed that those who meditated the most were most likely to belong to Profile 3, the *moderately non-judgmental* group, than any other profile. Note that this profile also had slightly above average global level of mindfulness. So, the prediction that experienced meditators would be most likely to belong to a profile with above average global level of mindfulness was supported by our data. Non-meditators were no more likely to belong to Profile 3, the *moderately non-judgmental* group (with above average global level of mindfulness) than Profile 2, the *average mindfulness* group, which had average levels of the specific factors of mindfulness but slightly below average level of the global mindfulness factor. Within-profile predicted probabilities indicated that the probability of being a member of Profile 4, the *judgmentally observing* profile, increased with increasing levels of meditation practice, whereas there was far less differentiation in the probability of being a member of Profile 1, the *non-judgmentally aware* group, as a function of meditation practice. However, as noted previously, those who reported meditating the most were more likely to be in Profile 3 (*moderately non-judgmental*) than in Profile 4 (*judgmentally observing*).

We did not have any a priori hypotheses about the links of the demographic predictors of age and gender with profile membership, so we can only draw preliminary conclusions at this stage. Nevertheless, our results indicate meaningful differences between the profiles as a function of the demographic variables, including meditation practice, lending initial support to the practical utility of the profiles identified in Model D.

Predicting outcomes from profile membership

We next sought to investigate the extent to which the profiles added value to the prediction of life effectiveness and mental health, over and above the predictive power of the six scale scores (Research Question 3). Mixture models in M*plus* provide class membership probabilities for each individual. Instead of using an 'all-or-none' approach of assigning class membership to participants based on the highest probability for one of the profiles, we employed a more sensitive, graded approach: using each individual's estimated probability of membership for each class as sampling probabilities, we created 25 imputations of class membership and combined them with the 25 imputations of the original sample. This allowed us to account for uncertainty in the latent class membership as well as the original multiple imputations of the outcome variables. We then used the commonly used delta method (Fox & Weisberg, 2010) to test the differences in the levels of the outcome variables in the four profiles. The delta method is a means of approximating standard errors for a transformation of a set of parameters where the variance–covariance matrix of the parameters is known (Oehlert, 1992). In the current case, the transformation of interest was the calculation of group-specific effects on the outcome of interest (given standard dummy coding, regression parameters for group membership estimates related to the difference from the reference group rather than the difference from zero).

We ran models of class membership predicting the outcome variables with and without controlling for the standardized scores of the various facets of mindfulness. Because Model A has been utilized in past research (Pearson et al., 2015), we conducted these tests on both the 'traditional' Model A and our B-ESEM-based Model D that replicated the *judgmentally observing* and *non-judgmentally aware* profiles observed in past research and our Model A.

Mental ill-health

Figure 4 contains the omnibus F-tests and depicts the point estimates and confidence intervals (the darker lines are 90% CIs and the lighter lines are 95% CIs) for mental ill-health in each of the profiles of Models A (the top panels) and D (the bottom panels). In the models without the scale scores as covariates (the left panels of Figure 4), Profile 4 has the highest score of mental ill-being. In the plots of estimates from models in which the scale scores were added as covariates (the right panels of Figure 4), the differences between Profiles 1 and 3 disappear, but Profile 4 continues to show the highest scores on mental ill-health. Whether we look at the results of Model A (the profiles derived using FFMQ scale scores) or Model D (the profiles derived using indicators from a B-ESEM of FFMQ and NAS-7), the conclusion is the same: the members of Profile 4—the *judgmentally observing* group (high on observing and non-reactivity, but low on non-judging and acting with awareness)—have the poorest mental health of all. Thus, in this instance, the LPAs based on the traditional approach (Model A) and our B-ESEM approach (Model D) yield similar results.

Satisfaction with life

Figure 5 depicts the results for satisfaction with life as a function of profile membership for Models A and D. In the top left panel of the figure, Profiles 1, 2, and 4 do not differ from each other, but Profile 3 shows higher life satisfaction than others. However, when the scale scores of FFMQ are added as covariates in the model (the right panel of Figure 5), there is no difference between the four profiles

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Table 6. Results of multinomial logistic regression models with the different categories of meditation practice predicting membership in the latent profiles of Model D

	Non-meditators (intercept)				Meditate <2 h/week				Meditate 2–4 h/week				Meditate >4 h/week			
	Estimate	*SE*	*p*	OR [95% CI]	Estimate	*SE*	*p*	OR [95% CI]	Estimate	*SE*	*p*	OR [95% CI]	Estimate	*SE*	*p*	OR [95% CI]
Profile 1 as a reference category																
Profile 2	1.56	0.05	<.001	4.76 [4.66 4.86]	0.32	0.16	0.06	1.38 [1.06 1.69]	0.82	0.34	0.03	2.27 [1.60 2.94]	0.90	0.48	0.10	2.45 [1.52 3.40]
Profile 3	1.56	0.05	<.001	4.76 [4.66 4.86]	0.32	0.16	0.06	1.38 [1.06 1.69]	1.02	0.33	<.001	2.77 [2.13 3.42]	1.56	0.47	<.001	4.76 [3.84 5.68]
Profile 4	−0.31	0.06	<.001	0.73 [0.61 0.85]	1.21	0.18	<.001	3.35 [3.00 3.71]	2.49	0.34	<.001	12.06 [11.39 12.73]	3.09	0.48	<.001	21.98 [21.04 22.92]
Profile 2 as a reference category																
Profile 1	−1.56	0.05	<.001	0.21 [0.11 0.31]	−0.32	0.16	0.06	0.73 [0.41 1.04]	−0.82	0.34	0.03	0.44 [−0.23 1.11]	−0.90	0.48	0.10	0.41 [−0.53 1.35]
Profile 3	0.00	0.03	0.70	1.00 [0.94 1.06]	−0.01	0.08	0.78	0.99 [0.83 1.15]	0.20	0.13	0.15	1.22 [0.97 1.48]	0.66	0.17	<.001	1.93 [1.60 2.27]
Profile 4	−1.88	0.05	<.001	0.15 [0.05 0.25]	0.89	0.12	<.001	2.44 [2.20 2.67]	1.67	0.15	<.001	5.31 [5.02 5.61]	2.19	0.18	<.001	8.94 [8.58 9.29]
Profile 3 as a reference category																
Profile 1	−1.56	0.05	<.001	0.21 [0.11 0.31]	−0.32	0.16	0.06	0.73 [0.41 1.04]	−1.02	0.33	<.001	0.36 [−0.29 1.00]	−1.56	0.47	<.001	0.21 [−0.71 1.13]
Profile 2	0.00	0.03	0.70	1.00 [0.94 1.06]	0.01	0.08	0.78	1.01 [0.85 1.17]	−0.20	0.13	0.15	0.82 [0.56 1.07]	−0.66	0.17	<.001	0.52 [0.18 0.85]
Profile 4	−1.88	0.05	<.001	0.15 [0.05 0.25]	0.89	0.12	<.001	2.44 [2.20 2.67]	1.47	0.15	<.001	4.35 [4.06 4.64]	1.53	0.16	<.001	4.62 [4.30 4.93]
Profile 4 as a reference category																
Profile 1	0.31	0.06	<.001	1.36 [1.25 1.48]	−1.21	0.18	<.001	0.30 [−0.05 0.65]	−2.49	0.34	<.001	0.08 [−0.58 0.75]	−3.09	0.48	<.001	0.05 [−0.90 0.99]
Profile 2	1.88	0.05	<.001	6.55 [6.46 6.65]	−0.89	0.12	<.001	0.41 [0.18 0.65]	−1.67	0.15	<.001	0.19 [−0.11–.48]	−2.19	0.18	<.001	0.11 [−0.24 0.46]
Profile 3	1.88	0.05	<.001	6.55 [6.46 6.65]	−0.89	0.12	<.001	0.41 [0.18 0.65]	−1.47	0.15	<.001	0.23 [−0.06 0.52]	−1.53	0.16	<.001	0.22 [−0.10 0.53]

Note. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*. SE: standard error; OR: odds ratio; CI: Confidence Interval.

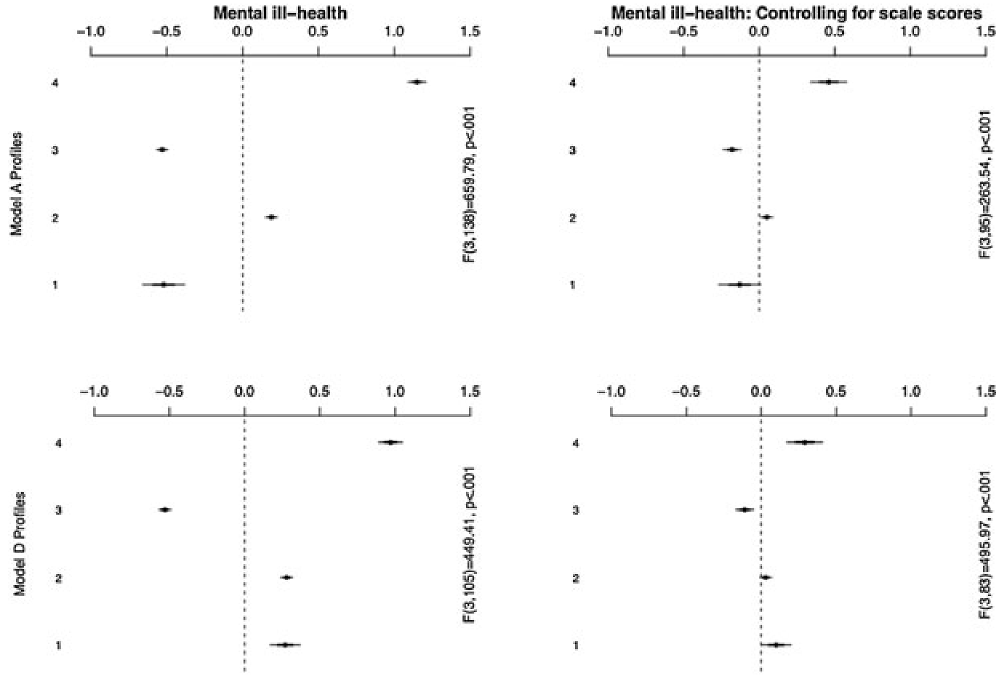

Figure 4. Mental ill-health as a function of profiles of Model A (top panels) and Model D (bottom panels) without (left panels) and with (right panels) controlling for the scale scores. The omnibus F-test of latent profile membership in each model is reported on the right of the model's respective panel. The darker lines are 90% CIs, and lighter lines are 95% CIs. Model A Profile 1: *Non-judgmentally aware*; Model A Profile 2: Low mindfulness; Model A Profile 3: High mindfulness; Model A Profile 4: *Judgmentally observing*. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*.

of Model A in terms of life satisfaction. In contrast, Model D profiles differ on life satisfaction even when the scale scores are added as covariates (the bottom right panel), but the differences between Profiles 2 and 3 are no longer present. Profile 4 shows higher life satisfaction relative to other profiles. Thus, the B-ESEM derived profiles appeared to predict unique variance in life satisfaction, over and above the scale scores, whereas the traditional approach did not.

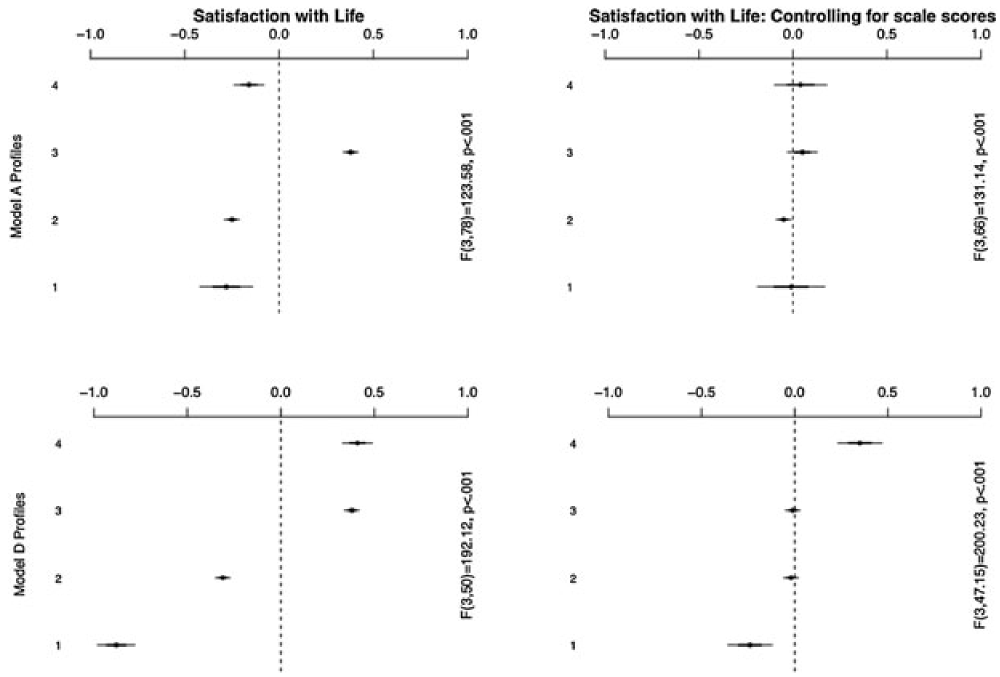

Figure 5. Satisfaction with life as a function of profiles of Model A (top panels) and Model D (bottom panels) without (left panels) and with (right panels) controlling for the scale scores. The omnibus F-test of latent profile membership in each model is reported on the right of the model's respective panel. The darker lines are 90% CIs, and lighter lines are 95% CIs. Model A Profile 1: *Non-judgmentally aware*; Model A Profile 2: Low mindfulness; Model A Profile 3: High mindfulness; Model A Profile 4: *Judgmentally observing*. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*.

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Life effectiveness

The pattern of results for life effectiveness was similar to that of satisfaction with life, as shown in Figure 6. In the plots of Model A (the top panels), adding the scale scores as covariates removed the observed differences between Profile 4 and other profiles, but in the plots of Model D (the bottom panels), Profile 4 continued to show higher levels of life effectiveness especially when controlling for the scale scores. The clearest conclusion from this figure is that the B-ESEM derived *judgmentally observing* profile uniquely predicted life effectiveness, whereas the traditionally derived *judgmentally observing* profile did not.

In sum, in response to our Research Question 3—whether or not the mindfulness profiles predict variance in outcomes even after controlling for the scale scores—the traditionally derived profiles of Model A did not pass this test consistently for all three outcomes but the B-ESEM derived profiles of Model D did. The person-centred approach of Model D, but not Model A, consistently added value to a purely variable-centred prediction of the outcomes.

DISCUSSION

Using the Occam's razor, we made a rather strong claim in the Introduction section of this paper that a person-centred approach to examining mindfulness should add value to a purely variable-centred approach in predicting theoretically relevant outcomes, or it should be abandoned in favour of the parsimonious variable-centred approach. We conducted an extremely conservative test of added value, in that we required the profiles to predict variance in outcomes over and above the scale scores of mindfulness. We found that the test was passed only when the data were modelled using a B-ESEM framework that separates level and shape effects in profiles. One of our core findings is that a subgroup of people—the *judgmentally observing* group—showed a divergent profile, being high in observing and non-reactivity but low in non-judgment and acting with awareness aspects of mindfulness. Even after controlling for scale scores, which reliably related to the outcomes, this group continued to differ from other profiles in terms of mental health, satisfaction with life, and life effectiveness.

We began our investigation with three specific questions: (i) Would the four profiles of mindfulness identified in previous research emerge in our sample when we disentangle the level and shape effects in the profiles? (ii) Does adding nonattachment to the five factors of mindfulness lead us to identify profiles that differ from those that have been identified in the past? (iii) Do mindfulness profiles predict variance in mental health and functioning, even after we control for the specific mindfulness variables? We first replicated the four profiles of mindfulness previously identified in other research (Bravo et al., 2016; Pearson et al., 2015) in our LPA based on the standardized scale scores of the five subscales of FFMQ (our Model A). We then attempted to answer our first research question by disentangling the level and shape effects by using the factor scores from a B-ESEM of FFMQ as indicators in our second set of LPAs: although the 4-profile solution in this case

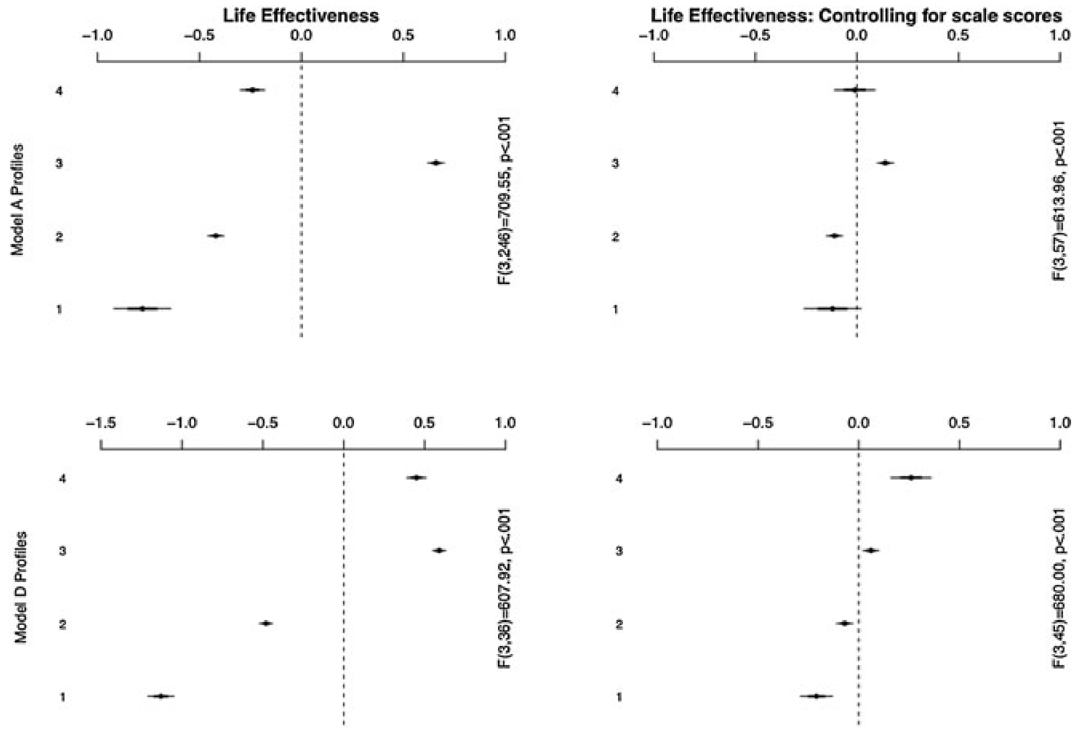

Figure 6. Life effectiveness as a function of profiles of Model A (top panels) and Model D (bottom panels) without (left panels) and with (right panels) controlling for the scale scores. The omnibus F-test of latent profile membership in each model is reported on the right of the model's respective panel. The darker lines are 90% CIs and lighter lines are 95% CIs. Model A Profile 1: *Non-judgmentally aware*; Model A Profile 2: Low mindfulness; Model A Profile 3: High mindfulness; Model A Profile 4: *Judgmentally observing*. Model D Profile 1: *Non-judgmentally aware*; Model D Profile 2: *Average mindfulness*; Model D Profile 3: *Moderately non-judgmental*; Model D Profile 4: *Judgmentally observing*.

DOI: 10.1002/per

(Model B) was reasonable and yielded the *judgmentally observing* group previously identified in Model A, the *non-judgmentally aware* group failed to emerge in this model.

We proceeded to our second research question regarding nonattachment and conducted a set of LPAs that included nonattachment as a sixth aspect of mindfulness. In parallel to Model A, we first used the standardized scale scores of the five aspects of mindfulness and the sixth aspect of nonattachment as indicators in mixture models: the 4-profile solution (Model C) yielded the *judgmentally observing* group but the other profiles were poorly defined. Our final set of LPAs helped shed further light on our Research Questions 1 and 2: in an LPA using the factor scores from a B-ESEM of FFMQ and NAS-7, both the *judgmentally observing* and the *non-judgmentally aware* groups were clearly evident in a 4-profile solution (Model D), but there was no clear evidence for all-high or all-low mindfulness groups in this solution, as has been found in previous research (Bravo et al., 2016; Pearson et al., 2015). Instead, there were two groups, the *average mindfulness* and *moderately non-judgmental* profiles, which showed slightly lower and higher levels of the global mindfulness factor, respectively.

Demographic variables meaningfully predicted profile membership of Model D. Compared to older participants, younger participants, particularly younger males, were slightly more likely than females to belong to the *judgmentally observing* group. Meditation practice was also meaningfully related to profile membership. Between-profile predicted probabilities results showed that those who meditated the most were most likely to be in the profile that had above average levels of global mindfulness, the *moderately non-judgmental* profile, than any other profile. In contrast, non-meditators were no more likely to be in the *moderately non-judgmental* profile than the *average mindfulness* profile, which had a slightly below average global mindfulness level. Within-profile predicted probabilities yielded one unexpected finding: for meditators in the *judgmentally observing* group, the probability of being a member of this profile increased with increasing levels of meditation practice. This finding was surprising. At least for a small subpopulation (9% of our sample), increasing levels of meditation do not necessarily increase awareness and non-judgmental attitudes towards one's internal states —the qualities that are expected to increase through meditation practice. It is possible that the meditators in the *judgmentally observing* profile in our sample engaged in meditation practices that did not involve non-judgment the way it is described in the scientific literature on mindfulness and measured by the FFMQ.

Also, note that the *judgmentally observing* group, compared to other groups, had the highest mean for the specific factor of observing. Most meditation traditions recommend extensive practice with focused attention on the body and the breath, which mainly involves observing the sensations that arise in the body with the breath, before attempting to bring greater mindful awareness to states of mind (Lutz, Slagter, Dunne, & Davidson, 2008). Therefore, it is plausible that among the meditators in the *judgmentally observing* group, increasing levels of meditation practice reflected an increase in focused attention and observing somewhat divorced from other qualities of mindfulness. Future studies are needed to clarify the link between meditation and the different profiles of mindfulness by obtaining detailed information about the nature and duration of meditation in which participants engage.

Perhaps, most strikingly, the *judgmentally observing* group in Model D scored higher than other profiles, which did not differ from each other, on relevant outcome variables in the most conservative of all tests in which profile membership was used to predict outcomes controlling for the standardized scale scores of the six subscales (Research Question 3). Members of this profile, compared to other profiles, scored higher on mental ill-health, satisfaction with life, and life effectiveness. Interestingly, when we conducted similar conservative tests on profile membership of Model A (based on standardized scores of FFMQ alone) on the same outcomes, the *judgmentally observing* group showed higher mental ill-health, but the four profiles did not differ in terms of life satisfaction and life effectiveness.

In other words, the person-centred approach of Model A perfectly replicated previously observed profiles but failed to add value to a purely variable-centred approach in predicting satisfaction with life and life effectiveness. In contrast, Model D profiles only partially replicated previously identified profiles but continued to predict the outcomes even after controlling for scale scores. These results imply that past research may have overstated the value of the four profiles extracted using the traditional method of using scale scores of FFMQ as indicators in profile analysis. In our sample, the profiles derived using this traditional method did not add value above and beyond the scale scores of the FFMQ. When we included the full range of mindfulness scales in the mix, including nonattachment, and disentangled the level and shape effects in B-ESEM, we identified a *judgmental observing* group that was predictive of outcomes over and above the scale scores. Consistent with recent research (Sahdra, Ciarrochi, & Parker, 2016a), our results highlight the importance of assessing nonattachment for a more complete conceptualization of mindfulness.

It is noteworthy that the *judgmentally observing* group consistently emerged in all Models A to D. Further, this group was the only one different from the other profiles in terms of the outcome variables in the conservative tests of profile membership in Model D predicting the outcomes controlling for scale scores. In short, the most robust conclusion from the current study appears to be that people in the general population can be characterized by qualitatively different profiles of mindfulness, with about 9% of people corresponding to the *judgmentally observing* profile with scores high on observing and non-reactivity but low on non-judging and acting with awareness, despite average scores on the global level of mindfulness.

The *judgmentally observing* individuals, compared to other participants, reported the highest life satisfaction *and* highest mental ill-being, and they appear to live life most effectively. The differences in the levels of the outcomes between the other three profiles disappeared in the models that controlled for scale scores. The fact that the *judgmentally*

DOI: 10.1002/per

observing group had high levels of both negative and positive outcomes may seem puzzling at first. However, the finding is consistent with past research showing that mental ill-health and flourishing do not fall on a single bipolar continuum, rather they are separate unidimensional constructs (Keyes, 2005). Thus, having high levels of one dimension does not necessarily entail having low levels of another. In our own sample, the correlation of mental ill-health with life satisfaction was −0.33, and with life effectiveness was −0.28, suggesting that less than 10% of variance in mental ill-health in our sample overlapped with life effectiveness or satisfaction with life. Thus, it is possible for some people to show high levels of both mental ill-health and positive life outcomes, as we found to be the case in the *judgmentally observing* profile. Our findings are also consistent with other research that has identified high affect intensity individuals who tend to manifest more intense emotional responses when exposed to a variety of emotion-eliciting events (Harris & Moore, 1990). We speculate that judgmental observing might lead people to react more strongly to both positive and negative stimuli, thereby increasing both joy and sorrow. Future research is needed to more directly examine the link between judgmental observing and individual differences in affect intensity, mental health symptomology, and eudemonic well-being.

While comparing our study to past research on mindfulness profiles (Bravo et al., 2016; Pearson et al., 2015), it is important to note the differences and similarities between their and our research. First, the outcome variables in their and our research are different. For instance, they did not examine life satisfaction and life effectiveness, as we did, but we did not measure worry and rumination, as they did. It is therefore impossible to make inferences about the wide set of variables they used based on the results of our study. Also note that Bravo et al. (2016) and Pearson et al. (2015) used college student samples consisting primarily of young adults whereas we employed a nationally representative sample of American adults with a wide age range. Despite the different samples, a key similarity between our and their research is that in our Model A, which used the same method of profile extraction as did Bravo et al. (2016) and Pearson et al. (2015), we were able to replicate the shape of the profiles of the mindfulness facets that they had discovered.

Most importantly, we were able to extend Bravo et al.'s (2016) and Pearson et al.'s (2015) research by using a state-of-the-art method of disentangling the level and shape effects in latent profiles. Our Model B employed factor scores from a B-ESEM of the FFMQ as indicators of LPA. Our Model D employed factor scores from a B-ESEM of FFMQ and NAS-7, thus broadening the spectrum of measurement of mindfulness facets by including nonattachment (Sahdra, Ciarrochi, & Parker, 2016a). The shapes of two profiles in our Models B and D were comparable to the *non-judgmentally aware* and *judgmentally observing* groups reported by Pearson et al. (2015) and Bravo et al. (2016) and replicated in our Model A, but there was no clear evidence for groups that showed high or low levels on all specific factors. Further, after controlling for scale scores, only the *judgmentally observing* group significantly differed from the other profiles, which did not differ from each other, in terms of mental ill-health, satisfaction with life and life effectiveness. But, as acknowledged above, our inferences are limited to the set of outcome variables we employed. Future studies on latent profile analysis of mindfulness and nonattachment need to incorporate other theoretically relevant variables, such as, decentering (a shift in perspective from one's thoughts or emotions; Fresco et al., 2007), purpose in life (Ryff, 1989; Ryff & Keyes, 1995), self-distancing and wise reasoning (Grossmann, Sahdra, & Ciarrochi, 2016), and self-regulation strategies such as sustained attention (MacLean et al., 2010) and response inhibition (Sahdra et al., 2011), to test whether profile membership meaningfully predicts these outcomes.

Our person-centred results have potential clinical utility. The finding of qualitatively distinct groups cautions against thinking of mindfulness in a simple 'more or less' way. Rather, it is how the different mindfulness skills combine in a person that may be most important for his or her mental health. For example, the observing skills may be associated with better mental health for some people (those with relatively high levels of non-judging and acting with awareness), but worse for others (those with low levels of non-judging despite close to average levels on other mindfulness skills). These claims are consistent with past research that has yielded mixed results regarding the observing facet of mindfulness: for instance, observing is linked with low ill-health (Baer et al., 2008) in some studies but high levels of negative outcomes like anxious arousal (Desrosiers, Vine, Curtiss, & Klemanski, 2014) and dissociation (Baer et al., 2006) in other studies. They are also consistent with recent arguments that mindfulness may harm some people in some contexts (Ciarrochi, Atkins, Hayes, Sahdra, & Parker, 2016; Dobkin, Irving, & Amar, 2012). Our data suggest that mindfulness-based interventions that target the observing skills might inadvertently increase mental ill-health for some individuals. The situation is made even more complicated by the finding that judgmental observers appear to be highly sensitive to the good and the bad, experiencing greater highs (effective living and satisfaction with life) and lows (ill-mental health). An intervention that sought to reduce judgmental-observing might thus diminish positive experiences for some people. Our person-centred results therefore challenge the simple notion that mindfulness is like a 'Buddha Pill' (Farias & Wikholm, 2015), conferring benefit to all who learn it. Rather, we suggest that clinical practitioners need to look at each person's unique configuration of mindfulness skills, and how these skills are connected to the person's mental health and valued activities (see Ciarrochi et al., 2016, for a more detailed discussion of person-focused and contextualized approaches to interventions).

Based on our results, we suggest latent transition analyses, the longitudinal extension of LPA, as an important avenue for future researchers and clinicians. Latent transition analysis holds promise for examining the efficacy of mindfulness-based interventions as it allows the examination of transitions in latent class membership over time. For example, the goal of a mindfulness-based intervention can

DOI: 10.1002/per

be thought of as transitioning individuals from one of the less adaptive classes into one of the more adaptive classes.

We acknowledge that our study used self-report measures, which may be seen as a potential weakness of the study. However, our results cannot be easily attributed to response bias or shared method variance. The latent profile models using the factor scores of B-ESEM separate the specific factors from the global factor. To the extent that participants responded to the self-report measures in socially desirable way—presumably to score high on desirable attributes of mindfulness and low on undesirable ones—the global mindfulness factor statistically extracted that common tendency out of the scores of the specific factors, which continued to show configuration differences in Model D. Further, while examining the link between profile membership of Model D and the outcome variables, the fact that we controlled for the scale scores statistically removed the shared method variance in the mindfulness variables and the outcomes. Even with these strict controls, profile membership was reliably linked to the remaining variance in the outcomes. In sum, because we accounted for the global factor while extracting profile configurations in Model D, and controlled for the scale scores while examining the link between profile membership and the outcomes, the results of Model D are most likely due to the configuration differences in the shape of the profiles and less likely due to response bias or shared method variance that is common across all scales.

To conclude, our study demonstrates that about 9% of the population can be characterized by the *judgmentally observing* profile, and members of this group show mixed relationships with other variables. Our results also show that it is important to assess nonattachment for a clearer understanding of mindfulness as a multifaceted construct. Both variable-centred and person-centred approaches to studying mindfulness are important. But our person-centred analysis shows a distinctive advantage over a purely variable-centred approach. Mindfulness cannot be fully understood as 'more is better, less is worse.' People can be mindful in different ways.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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