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Latent profile analysis: A review and “how to” guide of its application within vocational behavior research

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ABSTRACT

Latent profile analysis (LPA) is a categorical latent variable approach that focuses on identifying latent subpopulations within a population based on a certain set of variables. LPA thus assumes that people can be typed with varying degrees of probabilities into categories that have different configural profiles of personal and/or environmental attributes. Within this article, we (a) review the existing applications of LPA within past vocational behavior research; (b) illustrate best practice procedures in a non-technical way of how to use LPA methodology, with an illustrative example of identifying different latent profiles of heavy work investment (i.e., working compulsively, working excessively, and work engagement); and (c) outline future research possibilities in vocational behavior research. By reviewing 46 studies stemming from central journals of the field, we identified seven distinct topics that have already been investigated by LPA (e.g., job and organizational attitudes and behaviors, work motivation, career-related attitudes and orientations, vocational interests). Together with showing descriptive statistics about how LPA has been conducted in past vocational behavior research, we illustrate and derive best-practice recommendations for future LPA research. The review and “how to” guide can be helpful for all researchers interested in conducting LPA studies.

Latent profile analysis (LPA) is an analytic strategy that has received growing interest in the work and organizational sciences in recent years (e.g., Morin, Bujacz, & Gagné, 2018; Woo, Jebb, Tay, & Parrigon, 2018). LPA is a categorical latent variable modeling approach (Collins & Lanza, 2013; Wang & Hanges, 2011) that focuses on identifying latent subpopulations within a population based on a certain set of variables (Collins & Lanza, 2013; Howard & Hoffman, 2018).[1] LPA thus assumes that people can be *typed* with

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[1] Although LPA is commonly classified as “person-centered” approach, and contrasted with a “variable-centered” approach in the literature, we here use “categorical latent variable model” instead of “person-centered” approach when referring to LPA, and use “continuous latent variable model” instead of “variable-centered” approach when referring to common factor analysis models. We do so because cross-sectional LPA does not investigate within-person development, and can be seen as complementary to a common factor analysis considering model correlations between variables across persons (Bauer & Curran, 2004; Muthén & Muthén, 2000). In fact, Molenaar and von Eye (1994) already recognized the equivalence of dimensional factor analysis models and categorical LPA models, noting that the model-estimated mean structure and covariance matrix for a CFA model containing k latent factors can be reproduced with $k + 1$ latent profiles in LPA. The major differences between LPA and a common factor

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varying degrees of probabilities into categories (subpopulations) that have different configural profiles of personal and/or environmental attributes. In particular, as Woo et al. (2018) pointed out, such categorical latent variable models allow a parsimonious representation of structures in the form of groupings. Given that categories and groupings are natural features of cognition due to the efficiency and simplicity they provide (Macrae & Bodenhausen, 2000), classification schemes derived from categorical latent variable models are conceptually meaningful and methodologically useful for developing and incorporating typologies based on data (Costa, Herbst, McCrae, Samuels, & Ozer, 2002).

Capitalizing on LPA methodological features and underlying assumptions, LPA has both the potential to address specific research questions, and to develop and expand theoretical thinking regarding the existence of different configurations of profiles in variables of interest to vocational behavior (e.g., work commitment, heavy work investment, or career adaptability), including their predictors and outcomes (e.g., Gillet, Morin, Sandrin, & Houle, 2018; Hirschi & Valero, 2015; Hom, Mitchell, Lee, & Griffeth, 2012). Although there were several calls to apply LPA strategies in work and organizational research (Gabriel, Campbell, Djurdjevic, Johnson, & Rosen, 2018; Wang & Hanges, 2011; Woo et al., 2018; Zyphur, 2009), the application of LPA in vocational behavior research is still in its infancy.

A recent review that covered LPA within major applied psychology and management journals identified only 37 studies that applied LPA (Woo et al., 2018). This relative scarcity, compared to continuous latent variable models (e.g., structural equation modeling based on a single population distribution) might be due to the unfamiliarity of thinking in categorical latent variable ways, or due to ambiguities about how to conduct and interpret LPA analyses (e.g., how to specify the models, or how to decide on the number of profiles). To help researchers capitalize on the strengths of, and be aware of potential problems and pitfalls of, using LPA in vocational behavior research, the present article aims to (a) review the existing applications of LPA within past vocational behavior research; (b) illustrate best practice procedures in a non-technical way of how to use LPA methodology, with an empirical example of different latent profiles of heavy work investment; and (c) outline future research possibilities in vocational behavior research based on LPA.

1. A brief introduction to latent profile analysis

LPA aims to identify *types*, or groups, of people that have different configural profiles of personal and/or environmental attributes. In the domain of vocational behavior, frequently these personal and environmental attributes are psychological constructs (e.g., different types of commitment, different dimensions of career adaptability, different types of perceived environmental support), so that LPA can also be described as identifying construct-based profiles (Woo et al., 2018). These profiles have also been termed classes, groups, or clusters in past research (Vermunt & Magidson, 2002; Wang & Hanges, 2011; Woo et al., 2018). Compared to traditional, non-latent clustering methods (e.g., k-means clustering, hierarchical clustering), LPA treats profile membership as an unobserved categorical variable, where its value indicates which profile an individual belongs to with a certain degree of probability. Specific advantages of LPA compared to traditional, non-latent clustering methods are that (a) individuals are classified into clusters based upon membership probabilities estimated directly from the model; (b) variables may be continuous, categorical (nominal or ordinal), counts, or any combination of these; and (c) demographics and other covariates can be used for profile description (Magidson & Vermunt, 2002).

LPA thus focuses on patterns of variables (also called LPA indicators). Profiles of individuals sharing similar patterns of variables are identified and compared with other profiles, both in terms of how the variables combine to form the profiles, and how those combinations are differentially related to predictors and outcomes (Collins & Lanza, 2013; Wang & Hanges, 2011). Hence, LPA is an ideal technique for addressing research questions that involve effects of qualitatively different configurations of many variables that cannot easily be represented by other methods, such as moderated regression analyses, with several interaction terms based on a single population distribution (Zyphur, 2009).

Qualitatively different configurations of variables are also known as shape differences between profiles (e.g., some profile indicators have relatively high levels above the sample mean and some others have relatively low levels below the sample mean in one profile and the other way around in another profile). Quantitatively different configurations of variables are also known as level differences between profiles (e.g., all profile indicators have relatively high levels above the sample mean in one profile and relatively low levels below the mean in another profile). For example, LPA has been successfully applied to the organizational commitment literature to examine combinations of four targets of commitment (affective, normative, high sacrifice, and lack of alternatives), and how these qualitative and quantitative combinations differentially relate to outcomes, such as turnover intentions and performance (Hom et al., 2012; Stanley, Vandenberghe, Vandenberg, & Bentein, 2013).

Although we provide a non-technical review about LPA, for the sake of completeness and clarity, we introduce a common LPA model equation as shown in Lazarsfeld and Henry (1968) or Peugh and Fan (2013):

(*footnote continued*)
analysis model is therefore the specified distribution of the underlying latent variables (discrete versus one of various possible continuous distributions), as well as the form of the relation between the latent variables and the observed variables (configural/distance-based for categorical latent variable models and linear/curvilinear for continuous latent variable models). For a review of different definitions of the "person-centered" approach, please see Woo et al. (2018) and Ployhart and Moliterno (2011), for the distinction between "person-centered" versus "person-specific" approaches see Howard and Hoffman (2018), and for the distinction between "categorical latent variable models" and "continuous latent variable models" see Bauer and Curran (2004), Molenaar and von Eye (1994), or L. K. Muthén and Muthén (2000).

$$\sigma_i^2 = \sum_{k=1}^{K} \pi_k (\mu_{ik} - \mu_i)^2 + \sum_{k=1}^{K} \pi_k \sigma_{ik}^2,$$

where μ_{ik} and σ_{ik} represent profile-specific (k) means and variances for variable i, and π_k indicates profile density, or the proportion of N participants that belong to profile k. LPAs assume (a) samples drawn from a heterogeneous population produce data that are a mixture of K profile-specific distributions; (b) observed y indicator variables are distributed normally; and (c) the profile-specific mean vectors μ_k are the profile-specific (k) observed variable means. If both separate mean vectors (μ_k) and separate covariance matrices (Σ_k) were freely estimated for all of the K latent profiles contained in the data, the number of estimated parameters would quickly increase as the number of observed variables increased. Therefore, two LPA model constraints are commonly imposed to model y variation with a minimum number of estimated parameters. First, the local independence assumption states that conditional on correct latent profile extraction or enumeration, all y are uncorrelated within each k latent profile, and all k-specific off-diagonal covariance matrix elements are zero. Second, the homogeneity assumption states that profile-specific covariance matrix elements along the main diagonal are constrained to equality across all k (i.e., $\Sigma_k = \Sigma, Y_k \sim N\ [\mu_k, \Sigma]$; Lubke & Neale, 2006; Vermunt & Magidson, 2002). Together, local independence and homogeneity assume that latent profile-specific (k) covariance matrices are diagonal and homogeneous, and that latent profiles differ only in their y-variable location (μ_k), not their y-variable relationship form (Σ; Lubke & Neale, 2006).

As mentioned earlier, LPA assumes population heterogeneity. It can be distinguished between observed heterogeneity and unobserved heterogeneity. Observed population heterogeneity occurs when subpopulations within the data can be defined in terms of a priori definable observed variables (e.g., gender or type of occupation). In this case, traditional multiple-group analytic techniques (e.g., *t*-tests, ANOVA, multi-group SEM, assuming population homogeneity) can be used to compare the observed groups. By contrast, unobserved population heterogeneity occurs when the variables that cause the heterogeneity are not observed a priori. In this case, subpopulations are latent (i.e., unobserved) and must be inferred from the data. LPA assumes unobserved heterogeneity, and that subgroups with specific subdistributions in key variables exist. Each subdistribution represents a latent profile, whose size is determined by its weight. Profiles can be differentiated by varying parameter values of their distributions in profile indicators (e.g., different means and variances between the identified profiles). Thereby, a given individual is assigned to the profile with the highest probability values for this given person (e.g., probability of 95% of belonging to profile A versus 5% of belonging to profile B). This probabilistic profile assignment is also called modal membership (Woo et al., 2018).

Regarding terminology, past research sometimes used the terms *latent class* and *latent profile* interchangeably—and sometimes differently, using the term latent class in cases where categorical indicators were analyzed, and latent profile where continuous indicators were analyzed for the formation of the latent categorical variable (Woo et al., 2018). In our review, we included studies that dealt with categorical and continuous indicators as long as they indicated a cross-sectional clustering of individuals to latent groups, and used the term LPA for both.

2. Overview: review of LPA applications, best-practice recommendations, and illustrative example

Because this article is also a how-to guide, we will address important issues that need to be considered when conducting LPA studies (e.g., Morin, Morizot, Boudrias, & Madore, 2011; Nylund, Asparouhov, & Muthén, 2007; Vermunt & Magidson, 2002; Woo et al., 2018): (a) determining an appropriate research question, (b) research design issues, (c) statistical issues, (d) deciding on the number of profiles, and (e) interpreting identified profiles. The ordering of these issues follows a logical flow starting from the beginning and planning of a study to the interpretation of findings. For each of those issues, we will provide (1) best practice recommendations from past research, (2) results of our literature review on LPA applications within past vocational behavior research, and (3) an application of the discussed issues to an illustrative example about heavy work investment. Before we start diving into the issues, we describe our literature search related to point (2) and introduce the illustrative example.

2.1. Literature search

To provide a summary of how often, why, and how LPA was applied within past research, we searched major vocational behavior-related journals (i.e., Career Development Quarterly, Career Development International, International Journal of Career Management, Journal of Career Assessment, Journal of Career Development, Journal of Counseling Psychology, and Journal of Vocational Behavior) for publications that applied LPA methods to answer any research question. To be comprehensive, we decided to apply a relatively broad search within title and abstract, using the following search terms: *latent profile**, *latent class**, *latent cluster**, *factor mixture model**, *mixture model**, *finite mixture*, *finite model**, *Gaussian mixture*, *binomial mixture*, *mixture*, and *person-centered*. We searched the entire time span until April 2019, which resulted in 257 articles.

In the next step, we screened these articles with the goal of identifying only those articles that, in fact, applied LPA within an empirical study with original data. For example, we excluded conceptual papers and articles that applied other categorical latent or non-latent variable models (i.e., growth mixture modeling, latent transition analysis, mixture regression analysis, or non-latent cluster analyses). Moreover, we excluded three articles that applied LPA, but solely investigated psychotherapy and clinical issues—and hence, not vocational behavior—resulting in 35 articles (that included a k of 46 studies because some articles presented multiple studies). An overview of general study characteristics and how LPA was applied in these studies is displayed in Table 1. The first study was published in 2009, and 82.6% of the studies were published in 2014 or later, showing that within vocational behavior research, LPA is a methodological approach emergerd within the past 10 years, with an increasing trend in the last five years.

2.2. Introducing the illustrative example: profiles of heavy work investment

The illustrative example of which we will refer throughout this article applies LPA to identify different profiles of heavy work investment. Specifically, we study three different components of heavy work investment: (a) working compulsively; (b) working excessively as two facets of workaholism (Clark, Michel, Zhdanova, Pui, & Baltes, 2016; Schaufeli, Taris, & Bakker, 2008); and (c) work engagement as a positive, fulfilling, work-related state of mind (Schaufeli, Bakker, & Salanova, 2006). Working compulsively and excessively represents more negatively connoted types of heavy work investment. Conversely, work engagement represents a more positively connoted type of heavy work investment (Schaufeli, Bakker, Van der Heijden, & Prins, 2009; Snir & Harpaz, 2012).

Data for this illustrative example stem from a research project focusing on young researchers' careers in Germany (i.e., research associates and postdoctoral researchers) with two measurement points (12 months apart, 70% response rate) to separate the latent profiles from investigated outcomes. The final sample consisted of 909 researchers from different academic disciplines, 480 (53%) female, mean age 33.23 years ($SD = 5.68$), and mean working hours of 44.35 ($SD = 10.34$) per week.

3. Determining an appropriate research question

3.1. Best-practice and review results

LPA is an approach that offers several methodological advantages, but should be applied in a theory-driven way, and not for the reason of solely applying a methodological approach with increasing popularity (Hom et al., 2012; Howard & Hoffman, 2018; Morin et al., 2011). In a first step, it should be plausible that the investigated topic can be seen as mixture of distributions with similar characteristics, and that the profile indicators that will be grouped together are indeed theoretically related, yet distinct, and have the potential to form different types of latent profiles. For example, it makes theoretical sense to investigate latent profiles based on different commitment components because commitment theory argues that the three components of commitment—affective, normative, and continuance—combine to form a commitment profile. Furthermore, theory proposes that behavior varies in predictable ways across profile groups (Meyer, Stanley, & Parfyonova, 2012). Hence, it seems plausible to assume that the observed data represents a mixture of different distributions of the three types of commitment. Moreover, commitment theory presumes different commitment foci (e.g., occupation, organization, and work group), and it is furthermore plausible to assume that these different commitment foci combine to form different foci profiles (Morin et al., 2011; Wombacher & Felfe, 2017), again suggesting that LPA is an appropriate method for investigation. Hence, before developing more specific research questions and conducting LPA analyses, authors should ensure that the selected variables that form the profiles have a strong conceptual basis. Besides relying on solid theory, it is also recommended to establish concept discrimination in a preliminary analysis (e.g., via EFA or CFA model comparisons) by showing that the conceptually expected factor structure emerges empirically among the variables that are used to form profiles (56.5% of the studies in our review did so).

A closer inspection of the LPA indicator variables that have been used in past vocational behavior research revealed seven different topic areas: (1) Job and organizational attitudes and behaviors, (2) work motivation, (3) career-related attitudes and orientations, (4) vocational interests, (5) work environments, (6) general personal characteristics, and (7) career interventions. A summary of the applied LPA indicators and categorization of all articles within this content scheme can be seen in Table 2 (a further description of these studies can be seen in the supplemental material).

Assuming it makes conceptual sense to apply LPA to a set of variables, there are some research questions that are typically investigated with LPA analyses: (1) How many and which profiles are in the data? (2) What is the prevalence (size) of each profile? (3) What predicts latent profile membership? (4) How do outcomes differ across profiles? and (5) Are the profiles replicable across distinct samples or time points? Different studies might be interested in one of these questions, or consider a combination of some or all of these questions. In any case, approaches might vary from purely exploratory (e.g., no assumptions about number of profiles, shape of profiles, or potential predictors) to fully confirmatory (e.g., clear assumptions or hypotheses about the number of profiles, size of profiles, or potential outcomes).

Within our review, the vast majority of studies were interested in the number and shape of profiles (80.4%), followed by researching outcomes (69.6%), and antecedents (37.0%) of profile membership. Although nearly all of the studies reported the size of the profiles, only 8.7% of the studies explicitly formulated a respective research questions in the beginning. Moreover, whereas 36.9% of the studies investigated at least one of their aims in an exploratory manner, 63.0% investigated at least one aim in a confirmatory manner. Furthermore, 39.1% of the studies formulated explicit hypotheses about the number and/or shape of profiles. From a theoretical perspective, this finding is not satisfying because is suggests that researchers do not provide or cannot draw on concrete theorizing to derive specific assumptions about how many and which profiles should be expected.

3.2. Illustrative example: research question

In the example presented here, the three main research questions attempted to (a) investigate the number and shape of latent profiles of heavy work investment, (b) investigate the prevalence of the identified profiles, and (c) validate the retained profile solution across a range of outcomes (criterion-related validity evidence). LPA is an appropriate strategy for analyzing heavy work investment because past theory (Aziz & Zickar, 2006; Gillet et al., 2018; van Beek, Taris, & Schaufeli, 2011) assumed that workaholism (i.e., working compulsively and excessively) and work engagement co-exist within persons, and thereby combine to form different configural profiles. Such assumptions are, for example, based on Self-Determination Theory (Deci & Ryan, 1991), which

Table 1
Overview of central study and LPA characteristics of the reviewed studies (k = 46).

Chracteristics	*k* (%) or median or mean
General study characteristics	
Region	
United States/North America	20 (43.5%)
Europe	19 (41.3%)
Australia/Oceania	4 (8.7%)
Asia	2 (4.3%)
Mix	1 (2.2%)
Sample description	
White-Collar	3 (6.5%)
Blue-Collar	2 (4.3%)
University students	19 (41.3%)
Students/apprenticeships	6 (13.0%)
Mix of workers	15 (32.6%)
Mix workers/students	1 (2.2%)
Cross-sectional predictors or outcomes	35 (76.1%)
Time-lagged predictors or outcomes	11 (23.9%)
Number of LPA indicators	M = 5.96 (SD = 6.97)
Number of extracted profiles	M = 4.50 (SD = 1.35)
Determining an appropriate research question	
How many and which profiles are in the data?	37 (80.4%)
What is the prevalence (size) of each profile?	4 (8.7%)
What predicts latent profile membership?	17 (37.0%)
How do outcomes differ across profiles?	32 (69.6%)
Exploratory	17 (36.9%)
Confirmatory	29 (63.0%)
Hypoptheses on number or shape of profiles	18 (39.1%)
Factor analysis on LPA indicators	26 (56.5%)
Research design issues	
Sample size	*Med* = 493.50; 131–16,280
Studies with $N > 500$	25 (54.3%)
Monte-Carlo/power analysis	0 (0%)
Criterion-related validity evidence (hypotheses on outcomes)	18 (39.1%)
Validity evidence by testing hypotheses on predictors on profile membership	8 (17.4%)
Comparison with continuous latent variable model approaches	4 (8.7%)
Replicability across different samples	18 (39.1%)
Replicability across different time points	3 (6.5%)
Multiple group LPA	2 (4.3%)
If replicated, successful	17 (81.0%)
If replicated, partly successful	2 (9.5%)
Statistical issues	
Individual data pre-analyses	19 (41.3%)
Type of estimator	
Maximul Likelihood (ML)	5 (10.9%)
Maximul Likelihood with robust standard errors (MLR)	23 (50.0%)
Unclear	18 (39.1%)
Missing data pattern evident	18 (39.1%)
If yes, Full Information	11 (61.1%)
If yes, Mulitple imputation	2 (11.1%)
If yes, Listwise deletion	5 (27.8%)
Local solutions	
Tested	21 (45.7%)
Unclear	25 (54.3%)
Deciding on the number of profiles	
Multiple fit values applied	45 (97.8%)
Mix of fit values and content decisions	31 (67.4%)
Error messages reported	0 (0%)
Out of bounce values reported	0 (0%)
Applied model fit values	
BIC (Bayesian information criterion)	36 (78.3%)
SABIC (Sample-adjusted BIC)	33 (71.7%)
AIC (Akaike information criterion)	27 (58.7%)
CAIC (consistent AIC)	14 (30.4%)
BLRT (bootstrapped likelihood ratio test)	28 (60.9%)
Adjusted LMR (adjusted Lo-Mendell-Rubin test)	27 (58.7%)
Entropy	31 (67.4%)
Posterior classification probabilities	22 (47.8%)

(*continued on next page*)

Table 1 (*continued*)

Chracteristics	*k* (%) or median or mean
Content decisions	
Discrimination	31 (67.4%)
Size of profiles	
Profiles < 1%	1 (2.2%)
Profiles < 3%	7 (15.2%)
Profiles < 25 cases	14 (30.4%)
Interpretation of profiles	
If assumptions (N = 18), assumptions confirmed	15 (83.3%)
If assumptions (N = 18), assumptions partly confirmed	2 (11.1%)

assumes that different types of motivation (e.g., autonomous versus controlled) that can be linked to workaholism and work engagement, and form different configural profiles. Moreover, conceptual models on workaholism assume that qualitatively different types of workaholism exist, combining subfacets of workaholism to form different profiles (Aziz & Zickar, 2006; Gillet, Morin, Cougot, & Gagné, 2017; Schaufeli et al., 2009; Spence & Robbins, 1992). For example, Spence and Robbins (1992) described a classification of workers with different types of workaholism, such as the true workaholic, the enthusiastic workaholic, or the relaxed worker, where they combined different components of heavy work investment. Past research already identified qualitatively and quantitatively different combinations among workaholism and work engagement components (Gillet et al., 2017; Gillet et al., 2018; Schaufeli et al., 2009; van Beek et al., 2011). Hence, altogether, it seems plausible to assume that the observed data of working compulsively and excessively, as well as work engagement, represents a mixture of different distributions of the three types of heavy work investment.

Hypothesis 1. There exist six ($3 \times 2 \times 1$) qualitatively (i.e., one or two indicators of heavy work investment with relatively low levels and one or two indicators of heavy work investment with relatively high levels, respectively) and three quantitatively (i.e., all indicators of heavy work investment with either low, medium, or high levels, respectively) different profiles of working compulsively, working excessively, and work engagement.

Hence, addressing the research question (a) of which and how many profiles exist was confirmatory. However, the exact prevalence of expected profiles was not described in past research in detail, and related results were divergent (Aziz & Zickar, 2006; Schaufeli et al., 2009; Snir & Harpaz, 2012). Hence, for our research question (b), we derived no concrete expectations about the size of the profiles within our sample.

To assess the profile indicator variables, we measured working compulsively and excessively with a German short-version of the *Dutch Work Addiction Scale* (DUWAS; Schaufeli, Taris, & Bakker, 2008). Work engagement was measured with the German short-version of the Utrecht Work Engagement Scale (Schaufeli et al., 2006). As recommended, we conducted a preliminary CFA with these scales. In the expected model, every scale represented one factor, and was indicated by the items of the scale. We compared this model with a model that included two factors (working compulsively and excessively as one factor, and work engagement as one factor), and a model that included one factor (all items of all scales loaded on one general factor). The three-factor model revealed the best fit of all models (all *p*-values of Chi-square comparisons below 0.05, final model: CFI = 0.95, RMSEA = 0.04).

4. Research design issues

4.1. Best-practice and review results

After defining the appropriate LPA research question and deciding whether to address these questions in an exploratory or confirmatory way, the next step was to make decisions about an appropriate research design.

4.1.1. Sample size

To decide on the proper size of a sample, researchers can rely on past research, rules of thumb, and statistical procedures to calculate power. Within our review, we identified a median sample size of 494 (with a broad range from 131 to 16,280). This suggests that a sample size around 500 seems reasonable, based on past research. Regarding rules of thumb, the simulation study of Nylund et al. (2007) concluded that a minimum sample size of about 500 should lead to enough accuracy in identifying a correct number of latent profiles. Within our review, 54.3% of the studies had a sample size larger than 500, and thus used a large enough sample when relying on a rule of thumb.

The most rigorous way of dealing with sample size issues would be to conduct Monte Carlo simulations to determine the power of specific sample sizes, or to decide on an appropriate sample size for a given power level (Dziak, Lanza, & Tan, 2014; Tein, Coxe, & Cham, 2013; Woo et al., 2018). Within our review, none of the studies mentioned that they conducted a Monte Carlo simulation; however, some studies did mention that they applied a large enough sample size (Leuty, Hansen, & Speaks, 2016), or that the results should be replicated with larger or more diverse samples (McLarnon, Carswell, & Schneider, 2015). We also do not expect that every content-driven study necessarily must conduct a power analysis because estimating power for LPA is a complex issue and requires knowledge of population parameter values for the simulation that emerges from prior work or theory, which is not always available.

4.1.2. Validation of profiles

When planning the research design of LPA studies, it is also important to consider how the derived profiles will be validated. There exist different strategies to do this. To establish criterion-related validity evidence, researchers might test mean differences across the profile groups in relation to theoretically relevant outcomes, which 39.1% of the included studies did. For example, Barbaranelli, Fida, Paciello, and Tramontano (2018) showed that different profiles of specific self-efficacy dimensions (task self-efficacy, empathic self-efficacy, and negative emotional self-efficacy) are differently associated with different criteria (in-role behavior, extra-role behavior, and counterproductive work behavior). Depending on the underlying causality assumptions, the variables for the criterion-related validity evidence might also be measured at a later point in time, and potentially controlled for their baseline levels (i.e., autoregressive effects) collected at the same time as the LPA indicators.

Next, researchers might examine predictors of profile membership as a source of validity evidence. Within our review, 17.4% of the studies formulated explicit hypotheses about predictors of latent profiles that could be interpreted as a type of profile solution validation (for an example of the Big Five and vocational interest profiles, see Perera & McIlveen, 2018).

Another possibility might be to test similarities and differences between LPA results and results from continuous latent variable model analyses (e.g., comparing differences in outcomes across latent groups versus results of regression analyses based on a single population distribution; Gabriel, Daniels, Diefendorff, & Greguras, 2015; Zyphur, 2009). We identified four articles (including five studies) that compared their results with other methodological approaches, for instance, with moderated regression analyses or non-latent clustering (cf. Dahling, Gabriel, & MacGowan, 2017; Gillet et al., 2018; Wang et al., 2018; Wombacher & Felfe, 2017). The results were mostly similar. However, such procedures should not be considered as standard procedures to validate LPA findings

Table 2
Overview of LPA research topics within past vocational behavior research.

Reference	LPA Indicators	Topic
Barbaranelli et al. (2018)	Work self-efficacy scale: task self-efficacy (SE), negative emotion SE, assertive SE, empathic SE, global SE	WM
Choi et al. (2015)	Career development and guidance and school success: career guidance curriculum, lectures on career development, department guide, career inventory, job shadowing, career counseling	CI
Dahling et al. (2017)	Feedback environment: source credibility, feedback quality, feedback delivery, frequency of favorable feedback, frequency of unfavorable feedback, source availability, promotes feedback seeking	WE
Deemer, Lin, Graham, and Soto (2016)	Stereotype threat: social identity, identity threat, science identity	WE
Ferguson and Hull (2018)	High school occupational preferences for science: science motivation, science attitude, science interest, science academic experiences	VI
Gerber, Wittekind, Grote, and Staffelbach (2009)	Schein's career anchors: being employable in a range of jobs, managing your own career, a short time in loss of organization, commitment to yourself and your career, a series of jobs at the same kind of level, living for the present, work as marginal to your life, a career is not important to you, spend what you've got and enjoy it	CAO
Gillet et al. (2018)	Workaholism, work engagement	WM
Graves, Cullen, Lester, Ruderman, and Gentry (2015)	Managerial work motivation: external motivation, introjected motivation, identified motivation, intrinsic motivation	WM
Haines et al. (2018)	Typology of part-time work: work characteristics: educational and experience requirements, work hours, supervision, pay level, flexibility, and permanent status and being employed elsewhere; role occupancy: having a partner, parenting, being a student, contribution to household income	WE
Herman, Trotter, Reinke, and Ialongo (2011)	Perfectionism: self-oriented striving, self-oriented critical, socially prescribed	GPC
Hirschi and Valero (2017)	Work motivation: chance events, career decidedness	CAO
Hirschi and Valero (2015)	Career adaptability: concern, control, curiosity, confidence	CAO
Holman et al. (2018)	Lesbian, Gay, Bisexual, and Transgender Climate Inventory: workplace support, workplace hostility	WE
Howard et al. (2016)	Motivation profiles at work: amotivation, external motivation, external-social regulation, introjected regulation, identified regulation, intrinsic motivation	WM
Johnson and Bouchard (2009)	Strong Vocational Interest Inventory, Jackson Vocational Interest Survey	VI
Leuty et al. (2016)	Blank–Strong-Campbell Interest Inventory, RIASEC, Leisure Interests Questionnaire Arts, Leisure Interests Questionnaire Competitive	VI
Lopez, McDermott, and Fons-Scheyd (2014)	Multiple life role planning: knowledge, commitment, independence, involvement	CAO
Mäkikangas (2018)	Job crafting: increasing one's structural job resources, decreasing one's hindering job demands, increasing one's social resources, increasing one's challenging job demands	JOAB
McLarnon et al. (2015)	RIASEC interests	VI
Meyer et al. (2015)	Organizational and supervisor commitment: organizational affective commitment, organizational normative commitment, organizational commitment lack of alternatives, organizational commitment high sacrifice, supervisor affective commitment, supervisor normative commitment, supervisor continuance commitment	JOAB
Meyer et al. (2012)	Organizational commitment and Supervisor commitment: affective commitment, normative commitment, continuance commitment	JOAB
Moeller et al. (2018)	Engagement, burnout	WM
Perera and McIlveen (2018)	RIASEC interests	VI
Perera and McIlveen (2017)	Adaptivity: neuroticism, extraversion, intellect/imagination, agreeableness, conscientiousness	GPC
Rice, Lopez, and Richardson (2013)	Perfectionism: conscientiousness, neuroticism; APS–R: high performance standards, discrepancy self-standards and actual performance	GPC
Rice, Ray, Davis, DeBlaere, and Ashby (2015)	Perfectionism: APS–R: high performance standards, discrepancy self-standards and actual performance, Frost Multidimensional Perfectionism Scale: personal standards, concern over mistakes	GPC

(*continued on next page*)

Table 2 (*continued*)

Reference	LPA Indicators	Topic
Rice and Richardson (2014)	Perfectionism: APS–R: High performance standards, discrepancy self-standards and actual performance; Frost Multidimensional Perfectionism Scale: concern over mistakes, personal standards, doubts about actions; Performance Perfectionism Scale: positive self-oriented perfectionism, negative self-oriented perfectionism	GPC
Rice and Taber (2019)	Perfectionism: high performance standards, discrepancy self-standards and actual performance	GPC
Richardson, Rice, and Devine (2014)	Perfectionism: high performance standards, discrepancy self-standards and actual performance, and reappraisal, suppression, anxiety, self-control, stress-reactivity increase in cortisol	GPC
Stanley et al. (2013)	Organizational commitment: affective commitment, normative commitment, perceived sacrifice commitment, few alternatives commitment	JOAB
Van Aerden, Moors, Levecque, and Vanroelen (2015)	Employment quality: type of employment contract, (low) material rewards, income level, non-wage benefits, (erosion of) workers' rights and social protection, uncompensated exceptional working times, (de)standardized working time arrangements, long working hours, schedule unpredictability, involuntary part-time employment, (limited) employability opportunities, training opportunities, collective (dis)organization, info on occupational health and safety issues, working times setting procedure, (in)balanced interpersonal power relations, employee involvement	WE
Valero and Hirschi (2016)	Work motivation: autonomous goals, positive affect, occupational self-efficacy	WM
Wang et al. (2018)	Perfectionism: APS–R: high performance standards, discrepancy self-standards and actual performance	GPC
Wombacher and Felfe (2017)	Affective organizational commitment, affective team commitment	JOAB
Woo (2011)	Career mobility attitudes: numbers of jobs quit, belief that persistence is a virtue (recoded), positive feelings about changing jobs regularly, belief that staying at one place too long leads to stagnation	CAO

Note. Job and organizational attitudes and behaviors (JOAB): LPA indicators related to cognitive or affective evaluations of an individual's relationship to his/her current job or organization, as well as behaviors targeted toward the job or organization;Work motivation (WM): LPA indicators related to how people are motivated to or are energized by their work; Career-related attitudes and orientations (CAO): LPA indicators related to resources or attitudes for career decision-making and career development; Vocational interests (VI): LPA indicators related to expressions of specific occupational interest domains; Work environments (WE): LPA indicators related to (perceptions of) characteristics of the work environment; General personal characteristics (GPC): LPA indicators related to relatively stable traits (not work specific), but have been investigated in relation to vocational behavior; Career interventions (CI): LPA indicators related to (attributes of) different types of career interventions.

because there are also conceptual and methodological reasons why continuous latent variable models versus categorical latent variable models and LPA versus non-latent clustering can lead to different results (Vermunt & Magidson, 2002; Zyphur, 2009). For example, only a few individuals with extreme values on some of the study variables might cause significant interaction effects within moderated regression analyses based on a single population distribution, leading to a biased picture (Gillet et al., 2018; Zyphur, 2009). Moreover, for several LPA indicators, replicating the findings on outcomes by moderated regression analyses based on a single population distribution can lead to a confusingly high number of interaction terms, for example, 121 interactions and 66 pages of supplemental material when considering seven dimensions of feedback environment (Dahling et al., 2017).

Finally, another important way of validating the final profile solution is to examine its replicability across different samples, contexts, and timepoints (Hirschi & Valero, 2015; Woo et al., 2018). In our review, 39.1% of the studies replicated the LPA solution with another sample, and 6.5% at another time point. From these studies, 81.0% fully replicated their initial results, whereas 9.5% partly replicated their initial results. A recently introduced approach is to apply multiple-groups LPA to simultaneously evaluate the similarity of latent profiles across groups based on statistical fit parameters (Morin, Meyer, Creusier, & Biétry, 2016), which was done by two articles in our review (Gillet et al., 2018; Perera & McIlveen, 2018). In sum, researchers planning to use LPA need to make careful decisions about which further variables and/or samples and/or timepoints to collect when planning their study.

4.2. Illustrative example

4.2.1. Sample size

The sample size in the illustrative example was 909. Hence, the sample size clearly exceeds the sample size suggested by past research (shared experience or rules of thumb). Moreover, the sample size is in line with recommendations form Monte Carlo simulations on the power of fit values within categorical latent variable modeling (Tein et al., 2013).

4.2.2. Validation of profiles

We decided to validate the profile solution with a comparison of two theoretically relevant outcomes across the identified profiles (i.e., criterion-related validity evidence), which were measured 12 months after measuring the indicators of the profiles. We decided to assess *burnout* and *perceived marketability* as outcome variables. *Burnout* can be defined as a state of exhaustion, disengagement from work, and a lowered sense of effectiveness as a professional (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001; Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1996). Recent conceptualizations focus upon two core dimensions of burnout: exhaustion and disengagement from work (Demerouti et al., 2001). Past research has shown that burnout can be explained by the experience of high job demands and maladaptive forms of work investment (Schaufeli, Taris, & van Rhenen, 2008; Shimazu, Schaufeli, & Taris, 2010). We assessed burnout because it is a frequently studied variable within vocational behavior (Moeller, Ivcevic, White, Menges, &

Brackett, 2018), and it is theoretically linked to the indicators of the profiles (Schaufeli, Taris, & van Rhenen, 2008). Perceived marketability is an individual's evaluation of contributing to organizational success and maintaining high employability within and across organizations (Eby, Butts, & Lockwood, 2003). Perceived marketability can be seen as one type of subjective career success in work environments nowadays (Eby et al., 2003). We assessed perceived marketability because previous studies have suggested that individuals work hard (i.e., show heavy work investments) to attain career benefits in terms of marketability or upward mobility (Burke & MacDermid, 1999; Spurk, Hirschi, & Kauffeld, 2016). Moreover, compared to burnout, which is negatively connoted, perceived marketability has a positive connotation, and therefore we can expect opposite effects of our profiles. In terms of measurement, burnout was measured with the scale by Demerouti and Bakker (2008), and perceived marketability with the German version (Spurk, Kauffeld, Meinecke, & Ebner, 2016) of the scale by Eby et al. (2003).

Based on Conservation of Resource Theory (Hobfoll, 1989), we assumed that profiles with only relatively high levels of working compulsively and excessively because potentially threatening and exhausting types of work investment show the most detrimental outcomes (high levels of burnout and low levels of marketability). Furthermore, because work engagement can be seen as a personal resource, we assumed that profiles where only work engagement shows relatively high levels will display the most beneficial outcomes (low levels of burnout and high levels of marketability). Furthermore, based on the Effort-Recovery Model (Meijman & Mulder, 1998) and a buffering assumption (van Beek et al., 2011), work engagement as a positive type of work investment (and resource) can reduce detrimental effects of negative types of work investment (i.e., working compuslively and excessively). In sum, we assume:

Hypothesis 2. Profiles with high levels of both working compulsively and excessively, and low levels of work engagement, are associated with the most detrimental outcomes (i.e., high levels of burnout and low levels of perceived marketability).

Hypothesis 3. Profiles with high levels of work engagement and low levels of working compulsively and excessively are associated with the most beneficial outcomes (i.e., low levels of burnout and high levels of perceived marketability).

Hypothesis 4. Profiles with high levels of work engagement and high levels of working compulsively and/or working excessively are associated with less detrimental outcomes (i.e., lower levels of burnout and higher levels of perceived marketability) than profiles with low levels of work engagement and high levels of working compulsively and/or working excessively.

5. Statistical issues

5.1. Best-practice and review results

After collecting data, the next important step relates to decisions about statistical issues in data modeling. The goal is to select the most appropriate statistical approach to analyze the data (e.g., selection of estimator, missing data treatment, and further issues, such as increasing the trustworthiness of the analysis).

5.1.1. Selection of estimator

A recommended way of deciding on which statistical estimator should be used is to analyze individual level data and descriptive statistics across relevant study variables (Berlin, Williams, & Parra, 2014). For example, if data are continuous, maximum likelihood (ML) estimation is appropriate. A further test is related to the distribution of individual values within the sample. If tests of multivariate normality indicate non-normal distributions, robust estimation strategies, such as ML with robust standard errors (MLR), are appropriate (Vermunt & Magidson, 2002).[2] Finally, extreme outliers might affect the estimation of the final profile solution and lead to extreme profiles with only a few cases (Vermunt & Magidson, 2002). To avoid such issues, an outlier analysis with the exclusion of some extreme cases is a solution (Hirschi & Valero, 2017).

Within our review, 41.3% of the studies reported a pre-analysis of raw data, such as the multivariate normality test, skewness, kurtosis, or outliers that might affect the results. Moreover, 50.0% of studies applied ML estimation with robust standard errors (MLR), whereas 10.9% applied ML, and for 39.1% of the studies, it remained unclear which estimator was used. However, as five studies modeled the LPA indicators with categorical data, we assume that these studies might have applied estimators other than MLR or ML.

5.1.2. Missing data treatment

Although we think that missing data treatment is an important issue in LPA research, we will not go into detail within this review. There exist several informative articles (Enders, 2008; Lanza & Cooper, 2016; Schafer & Graham, 2002) and books (Little & Rubin, 2020) on this issue, providing different solutions. One common recommendation is that missing data on variables relevant for the profile solution should be handled—if data is missing at random—with full information maximum likelihood estimation (FIML), or with procedures based on multiple imputation, instead of applying listwise or pairwise deletion (Berlin et al., 2014; Vermunt & Magidson, 2002). Within our review, 39.1% of the studies described missing data. From these studies, 61.1% applied a FIML solution, 11.1% multiple imputation, and 27.8% listwise deletion. Hence, although most studies that reported missing data applied commonly recommended procedures (Little & Rubin, 2020), for more than half of the studies, it was unclear whether missing data was an issue or not.

[2] For a more detailed guidance of LPA estimator selection, specifically if the data is not continuous, we recommend the work of Asparouhov and Muthén (2011), Dempster, Schatzoff, and Wermuth (1977), or Vermunt and Magidson (2002).

5.1.3. Global versus local solutions

One important aspect mentioned within model estimation in the context of LPA is the potential existence of local maxima or local solutions. The best-fitting solution for every profile is generally determined by the so-called log-likelihood parameter. The solution with the closets value to zero is at maximum, and considered to be the best-fitting solution (Berlin et al., 2014; Vermunt & Magidson, 2002). Within LPA, often multiple maxima exist, and therefore researchers should try to avoid a local solution (i.e., local maximum). One recommended procedure is to use multiple starting values to find the global solutions (i.e., global maximum). This can be interpreted as a replication of several local maxima solutions (Berlin et al., 2014). The best log-likelihood value should be replicated in at least two final-stage solutions. If this is not the case, local solutions might be an issue, and the number of random starts should be increased until the log-likelihood value can be replicated.

Within our review, 45.7% of the studies mentioned that they considered either the possibility of local maxima or that they varied or increased the random starts to avoid local solutions. For example, Howard, Gagné, Morin, and Van den Broeck (2016) used 7000 random sets of start values, 300 iterations for each random start, and the 200 best solutions retained for final stage optimization, as recommended by Hipp and Bauer (2006). In cases where the best log-likelihood for the final stage solution cannot be replicated, it can be useful to compare parameter estimates from several final stage optimized solutions (including solutions with log-likelihood values close to the highest value observed). For example, the random seed value for each solution can be used to regenerate the solutions for comparison (e.g., using the OPTSEED option in *M*plus). If the parameter estimates are different across the solutions, this might be indicative of an unstable solution. Although a considerable number of studies reported how they dealt with local solution problems, in 54.3% of the studies it remained unclear whether they did not guard against local solutions or just did not report such tests.

5.2. Illustrative example

5.2.1. Pre-analyses, selection of estimator, and missing data

The scales of working compulsively and excessively and work engagement can be treated as continuous variables (Halbesleben, 2010; Schaufeli, Taris, & van Rhenen, 2008). An inspection of the histograms, as well as the associated statistical parameters of kurtosis, skewness, and standard deviations of the work investment variables, suggested that the raw data were not normally distributed. Hence, we decided to apply MLR estimation. Because the data contained missing values due to dropouts over time (30%) and non-responses for some cases on specific variables, we took the FIML approach. Because outliers can bias the results of LPA, we checked for multivariate outliers using the Mahalanobis distance (for working compulsively and excessively, and work engagement), with a p-value of 0.001 used as a cutoff, and excluded eight (< 1%) cases (Holtom, Burton, & Crossley, 2012) to finally obtain the final sample size of 909.

5.2.2. Global solutions and random starts

To guard against local solutions, we increased the default settings in *M*plus and set the number of random starts to 7000 and the final stage optimizations to 200 (Hipp & Bauer, 2006). The estimation revealed no error messages, and the output provided the information that the highest (most close to zero) log-likelihood value was replicated. Hence, our results do not appear to be due to local maxima.

6. Deciding on the number of profiles

6.1. Best-practice and review results

The next important step in the LPA research process is the selection of the best fitting profile solution. This procedure is not always straightforward, and past research recommended to not only relying on statistical fit values, but also on theoretical and content-related considerations (Gabriel et al., 2015; Hirschi & Valero, 2017; Vermunt & Magidson, 2002; Woo et al., 2018). Moreover, there are different approaches to which steps should be taken first, second, and so on. A general rule is that multiple fit values, as well as content decision criteria, should be applied when deciding on the final profile solution. A possible order of decision steps was provided by Ram and Grimm (2009): (1) inspect estimation outputs for error messages, out-of-bound parameters, and theoretical plausibility, (2) compare remaining models using relative fit information criteria (e.g., Bayesian Information Criterion, BIC; Akaike Information Criterion, AIC), (3) evaluate models with respect to confidence with which individuals have been classified as belonging to one group or another (e.g., entropy), and (4) compare different likelihood ratio tests that quantify specific comparisons between the model of interest and a model with one fewer class. The order of these steps might be adapted.

Within our review, none of the studies reported that they explicitly accounted for error messages or out-of-bound values when deciding on the number of profiles. However, we interpret this finding that within most of these studies, no error messages or out-of-bound values emerged, or that it was clear to us that we could not continue with models that resulted in error messages. Besides this, most of the studies considered the recommendations about relying on multiple criteria when selecting their final LPA solution (97.8% applied multiple statistical fit values, and 67.4% applied a mix of statistical fit values and content-driven decisions).

6.1.1. Model fit values

Table 3 summarizes advantages and disadvantages of possible model fit values to determine the appropriate number of profiles. Within our review, 78.3% and 71.7% of the studies applied the BIC or sample size adjusted BIC (SABIC), respectively. The AIC was

Table 3
Overview of fit information criteria considered for the selection of latent profile analysis solutions.

Indicator + formula	Characterization	Choice criterion	Advantages	Disadvantages
BLRT (Bootstrapped likelihood ratio test; McLachlan and Peel, 2000) $LR = -2\{logL(\hat{\psi}_K) - \log L(\hat{\psi}_{(K+1)})\}$	A nested model test that compares neighboring models (e.g., k vs. k + 1 profiles). Uses bootstrap samples to evaluate the distribution of the log-likelihood difference test statistic (McLachlan & Peel, 2000).	A non-significant ($p > .05$) BLRT for a model with k + 1 profiles indicates that the solution is not superior to a k-profile solution and that the latter one should be retained.	Discussed as one of the most accurate fit indicators, superior to other likelihood ratio test procedures (Nylund et al., 2007). Quantifies the confidence in the obtained results with a *p*-value.	May overestimate the number of profiles, proposing a solution with too many profiles (Morin & Marsh, 2015). Needs to be evaluated with non-normal indicators (Morgan, Hodge, & Baggett, 2016).
Adjusted LMR (Adjusted Lo-Mendell-Rubin test; Lo, Mendell, & Rubin, 2001) $\text{LR}_{adjusted} = \frac{\text{LR}}{1 + [(p-q)\log n]^{-1}}$	Like BLRT, a nested model test that compares neighboring models (e.g., k vs. k + 1 profiles). Based on a weight sum of chi-squares with an adjustment (Lo et al., 2001).	A non-significant ($p > .05$) adjusted LMR test for a model with k + 1 profiles indicates that the solution is not superior to a k-profile solution and that the latter one should be retained.	Tables in Morgan et al. (2016) suggest that the adjusted LMR may be more robust and avoid over-extraction of profiles with non-normal indicators when compared to BLRT and BIC. Quantifies the confidence in the obtained results with a p-value.	Generally lower rates in detecting the correct number of profiles when compared to SABIC and BLRT (Nylund et al., 2007; Tofighi & Enders, 2008). Exception may be when indicators are skewed (Morgan et al., 2016).
AIC (Akaike information criterion; Akaike, 1987)[a] $\text{AIC} = -2\log L(\hat{\theta}) + 2k$	An information index based on the log-likelihood and the number of parameters. Sample size does not incur in this fit index.	Model with the lowest AIC value offers best fit.	May be slightly superior to select the correct number of profile with small samples (< 500) or when rare profiles are present (Morgan, 2015).	Discussed as inferior fit index (Nylund et al., 2007). The AIC can overestimate the number of underlying profiles (McLachlan & Peel, 2000; Morgan, 2015; Nylund et al., 2007; Tofighi & Enders, 2008).
BIC (Bayesian information criterion; Schwarz, 1978)	An information index based on the log-likelihood of a model, the number of parameters, and sample size. It penalizes for sample size (Tofighi & Enders, 2008).	Model with the lowest BIC value offers best fit.	*Discussed as an accurate index* (Morgan, 2015; Nylund et al., 2007) and is consistent – selects correct model with higher probability with increasing sample size (Tofighi & Enders, 2008).	May overestimate number of profiles with non-normally distributed indicators (Morgan et al., 2016). Underestimation of profiles, however, for small sample sizes (Celeux & Soromenho, 1996; McLachlan & Peel, 2000).

(*continued on next page*)

Table 3 (*continued*)

Indicator + formula	Characterization	Choice criterion	Advantages	Disadvantages
SABIC (Sample size-adjusted BIC; Sclove, 1987) $\text{SABIC} = -2LL + p\log(N+2)/24$	Bayesian Information Criterion with further sample size adjustment.	Model with the lowest SABIC value offers best fit.	*Discussed as an accurate index* (Henson, Reise, & Kim, 2007; Morgan, 2015; Nylund et al., 2007). Corrected when compared to BIC to avoid penalizing for sample size (Sclove, 1987).	May overestimate number of profiles, especially for non-normally distributed indicators (Morgan et al., 2016).
Posterior classification probabilities $p(\theta \mid x) = \frac{p(x \mid \theta)p(\theta)}{p(x)}$	Indicates the probability that cases are correctly classified into the correct profile instead of the “wrong” one.	Unambiguous, high classification probabilities for each profile (although we are not aware of cutoff value standards). Results of our review (shared experience) show a mean value of 0.80, comparable to entropy.	The quality with which cases are classified into profiles can be inspected for distinct groups. The overall “distinctness” can thus be evaluated for single profiles.	Does not offer a cut-off or decision criteria. Profile assignment error can be dependent on the mere number of profiles (Collins & Lanza, 2010).
Entropy (Celeux & Soromenho, 1996) $EN(\hat{\tau}) = -\sum_{i-1}^{N}\sum_{k-1}^{K}\hat{\tau}_{ik}\log\hat{\tau}_{ik}$	A composite that indicates the overall ability of a mixture model to return well-separated profiles (Celeux & Soromenho, 1996). A weighted average of posterior classification probabilities.	Higher entropy (up to perfect classification at value 1) indicates better fit. Reported cut-off of 0.80 or higher (Clark & Muthén, 2009). Cut-off of between 0.60 and 0.80 is also seen as appropriate (Jung & Wickrama, 2008; Muthén, 2004).	Offers a value of how well the single cases are attributable to each profile and thus of the accuracy with which cases are classified into their true profile for a profile solution.	Error in profile assignment (on which entropy is based on) may increase as a function of the number of profiles. Entropy can thus change based on the addition of profiles only (Collins & Lanza, 2010) and is consequently imprecise indicator for model selection (Henson et al., 2007). Discussion about cut-off criteria (Lubke & Neale, 2006).

Note. For more information on the respective formula of theses fit indices, we refer to the mentioned references in the table. Importantly, some of the indices for model enumeration and selection are not available under some modeling conditions. Availability of model fit indices needs to be evaluated in dependence of data type and software package.

[a] Derived from the AIC, the consistent AIC (CAIC) penalizes the value of -2 times the log likelihood of the model for the number of free model parameters using the sample size. The adjustment made to CAIC increases the penalty for model complexity, but it is not as commonly used as AIC as an information-based fit criteria (Morgan et al., 2016).

less frequently applied (58.7%, and 30.4% applied the consistent AIC (CAIC); Anderson, Burnham, & White, 1998). Regarding comparisons between the model of interest and a model with one fewer class, 60.9% of the studies applied the Bootstrapped Likelihood Ratio Test (BLRT) and 58.7% the adjusted Lo-Mendell-Rubin (LMR) test. Regarding the confidence with which individuals have been classified as belonging to one profile or another, 67.4% of the studies considered entropy values, whereas fewer (47.8%) reported posterior classification probabilities, mostly with values above the recommended threshold levels of 0.80 for each (Clark & Muthén, 2009; Haines, Doray-Demers, & Martin, 2018).

6.1.2. Content decisions

One aspect that should be considered is how well an additional profile can be discriminated from another that has already been retained (Berlin et al., 2014; Vermunt & Magidson, 2002). If the additional profile adds a substantial new variable formation (e.g., a qualitatively new profile) to the prior solution, the new profile might be retained. On the contrary, if an additional profile is relatively close to another profile in the prior solution (e.g., only minor level differences in all profile variables), and thereby adds no meaningful new insights, the new profile might not be retained due to reasons of parsimony (Berlin et al., 2014; Vermunt & Magidson, 2002). Expressed in other words, a general challenge for research applying LPA is to show that the latent profiles contribute to the understanding of the constructs and tell us something that we did not know before. Specifically, quantitative level effects can be easily accommodated in continuous latent variable models (e.g., main effects within regression analyses), whereas qualitatively different profiles are considered as "superior" in providing new and theoretically interesting information (Parker & Brockman, 2019). For example, Meyer, Morin, and Vandenberghe (2015) identified qualitatively different commitment profiles by showing that one group of people had high levels in normative and affective commitment, but low levels in continuance commitment, whereas another group had high levels in continuance commitment, but low levels in all other types.

About two-third of the studies (67.4%) mentioned that they considered profile discrimination issues when deciding on the number of profiles. Some studies also considered this criterion as the most important criterion, overruling statistical fit values. For example, when investigating profiles of feedback environment, Dahling et al. (2017) mentioned that although the four-profile solution had lower AIC and BIC statistics that made it a viable candidate, this profile structure exhibited a lower entropy value and yielded a profile solution with two redundant profiles, which was not of any particular theoretical interest. The authors thus retained the three-profile solution, although fit statistics would slightly prefer a four-profile solution.

An issue that also should be considered in terms of parsimony and meaningfulness is profile size. If an additional profile includes only a small number of cases, strong reasons are needed to argue for an addition of this profile, given the possibility of lower power, lower precision relative to the other larger profiles, and less parsimony (Lubke & Neale, 2006). A rule of thumb is if the additional profile includes < 1.0% of total sample size or fewer than 25 cases, the profile should be rejected (Lubke & Neale, 2006). However, only one study reported a profile with < 1% of the sample size (Gillet et al., 2018), and in this case, it was the replication of a profile which had a size above 1% in a different, larger sample. A series of studies (15.2%) reported at least one profile with a size of 3% or less, indicating that profiles between the size of 1% and 3% of the total sample are occasionally retained. However, even with the rule of having minimum 25 cases in the profile, 30.4% of the studies retained profiles consisting of < 25 cases. This again might be an artifact of a relatively small overall sample size and could be prevented by a priori planned larger sampling. Therefore, the percentage of overall sample size should be the preferred rule of thumb to be considered.

Finally, if the LPA is not used to fully address exploratory research questions, researchers should carefully align the potential different final solutions to the theoretically most meaningful solution, and give priority to the theoretically best-fitting solution (if the fit values allow for such). Overall, fit values might be overruled by theoretical decisions if different fit indices allow different final solutions. For example, a five-profile solution, including engagement and burnout, was retained (although fit indices slightly suggested another solution) because it replicated the expected profiles shown in studies on profiles among high school students (Moeller et al., 2018). In cases where researchers have strong and clear theoretical arguments about the number and the shape of profiles, confirmatory LPA with setting specific modeling constraints can also be the method of choice (e.g., Finch & Bronk, 2011; Schmiege, Masyn, & Bryan, 2018). None of the reviewed studies applied this approach.

6.2. Illustrative example

6.2.1. Procedure

For a clear interpretation of which indicator values are above or below the sample means, we used the z-standardized mean scale scores of working compulsively, working excessively, and work engagement, and conducted the LPA based on these three indicators. We used a stepwise approach to determine the number of latent profiles that best characterize the data and sample, starting with a LPA with two profiles and successively adding profiles (Nylund et al., 2007). In each step, we examined the fit information criteria from Table 4 (except posterior classification probabilities because they are redundant with entropy). In addition, we considered theoretical coherence (see Hypothesis 1), discrimination, and profile size for the decision on the final number of profiles.

6.2.2. Identification of number of profiles

We investigated the fit statistics for solutions with two to ten profiles (Table 4). We first considered the three-profiles solution, which showed the lowest BIC-value and a nonsignificant adjusted LMR-test when continuing to four profiles. Moreover, we considered the four-profiles solution because it showed a BLRT-value near the 0.05-criterion (p = .03 for the step from four to five profiles), and it showed high entropy. However, the SABIC and AIC values kept descending with additional profiles. Both the three- and the four-profiles solutions showed profiles that differed only in the overall level of the three indicators. Hence, both solutions

Table 4
Statistics for profile structures within the illustrative example.

No. of profiles	LL	FP	SABIC	BLRT(p)	LMR(p)	AIC	BIC	Entropy
2	−3678.01	10	7392.38	0.0000	0.0000	7376.01	7424.13	0.593
3	−3652.35	14	7355.61	0.0000	0.0022	7332.70	7400.07	0.622
4	−3642.36	18	7350.18	0.0000	0.2122	7320.72	7407.34	0.744
5	−3634.11	22	7348.22	0.0300	0.3609	7312.08	7418.08	0.657
6	−3624.45	26	7343.45	0.0000	0.5589	7300.90	7426.02	0.725
7	−3612.88	30	7334.85	0.0128	0.2909	7285.75	7430.12	0.723
8	−3604.93	34	7333.50	0.0400	0.0484	7277.86	7441.48	0.693
9	−3597.41	38	7333.01	0.0938	0.1420	7270.83	7453.70	0.711
10	−3590.49	42	7333.71	0.1579	0.3124	7264.98	7467.09	0.703

Note. BLRT(p) = p-Value for the bootstrapped likelihood ratio test. LMR(p) = *p*-Value for the adjusted Lo-Mendell-Rubin-test. FP = free parameters.

provided only *partial support* for fit criteria, and did not offer substantive interpretations of much theoretical interest (e.g., no qualitatively different models emerged). Therefore, we continued the examination of additional solutions, and finally decided the eight-profiles solution to be the most appropriate. Adding one more profile to this solution attained the first nonsignificant BLRT-value (p = .09). Furthermore, the eight-profiles solution had the second-to-lowest SABIC-value, with a ΔSABIC of below one, compared to the nine-profiles solution. The entropy value (0.69) showed that cases could be appropriately allocated to the correct latent profile with acceptable certainty, although the optimum size of 0.80 was not reached.[3] Moreover, no profiles of small size emerged in this solution (all profiles contained at least 3% of the total sample size). Finally, as assumed, the eight-profiles solution showed a number of qualitatively different profiles of theoretical interest that furthermore are relatively different in content. However, we did not identify a profile where all three indicators were at medium levels. Therefore, Hypothesis 1 was partially supported. Fig. 1 depicts the standardized means of working compulsively, working excessively, and work engagement for the selected eight-profiles solution.

7. Interpretation of latent profiles

7.1. Best-practice and review results

After carefully deciding on the final profile solution, one last step within the LPA research process is to interpret the retained solution. Researchers should inspect the content of the single clusters and assign labels to the single profiles. Such names might be directly related to the included indicators and the levels within the profiles, or aim to capture the essence of the respective profiles. In case of a large number of indicators and profiles, it might also make sense to number the profiles instead of assigning labels that cannot be readily discriminated verbally anymore. In any case, the final decision on such issues strongly depends on the investigated topic, complexity of the extracted profiles, and terms and labels used in the respective research fields. Hence, there are no clear rules compared to the more technical steps presented before. Within our review, we observed different strategies, from describing the content of the profiles by means of the indicators (Dahling et al., 2017; Moeller et al., 2018), by giving names capturing the essence of the profiles (Holman, Fish, Oswald, & Goldberg, 2018; McLarnon et al., 2015), or by solely numbering the profiles (Choi, Kim, & Kim, 2015).

Solid interpretations of the content and indicator values within profiles are especially important to support hypotheses on the number and shape of profiles. Within our review, from the 18 studies that included hypotheses about the number and/or shape of profiles, 15 studies (83.3%) fully confirmed these assumptions, and two studies (11.1%) partly confirmed these assumptions.

7.2. Illustrative example

7.2.1. Interpretation of extracted profiles

The first extracted group was of small to medium size (n = 56, 6%), and showed low levels in all three indicators. It can be characterized as the group of *low work investors* (see Fig. 1). The second group was of large size (n = 185, 20%), and characterized by low levels in working compulsively and working excessively, but above-average levels in work engagement. We called this group the *purely engaged* workers group. The third group was small (n = 37, 4%) and showed low values of working compulsively, the lowest values in working excessively, and average levels in work engagement. We called it the *idle workers* group. The fourth group was rather large (n = 135, 15%), and characterized by above-average levels of working compulsively, average levels of working excessively, and low levels of work engagement. We named this the *compulsive workers* group. The fifth group, the *high work investors* group, was large (n = 211, 23%) and showed high values in working compulsively, working excessively, and work engagement. The sixth group was the largest of all (n = 234, 26%), and had slightly below-average values in working compulsively, slightly above-average values in working excessively, and above-average values in work engagement. We called this the *engaged workers* group. The

[3] Muthén (2004) and Jung and Wickrama (2008) argued that entropy values between 0.60 and 0.80 were still in the acceptable range.

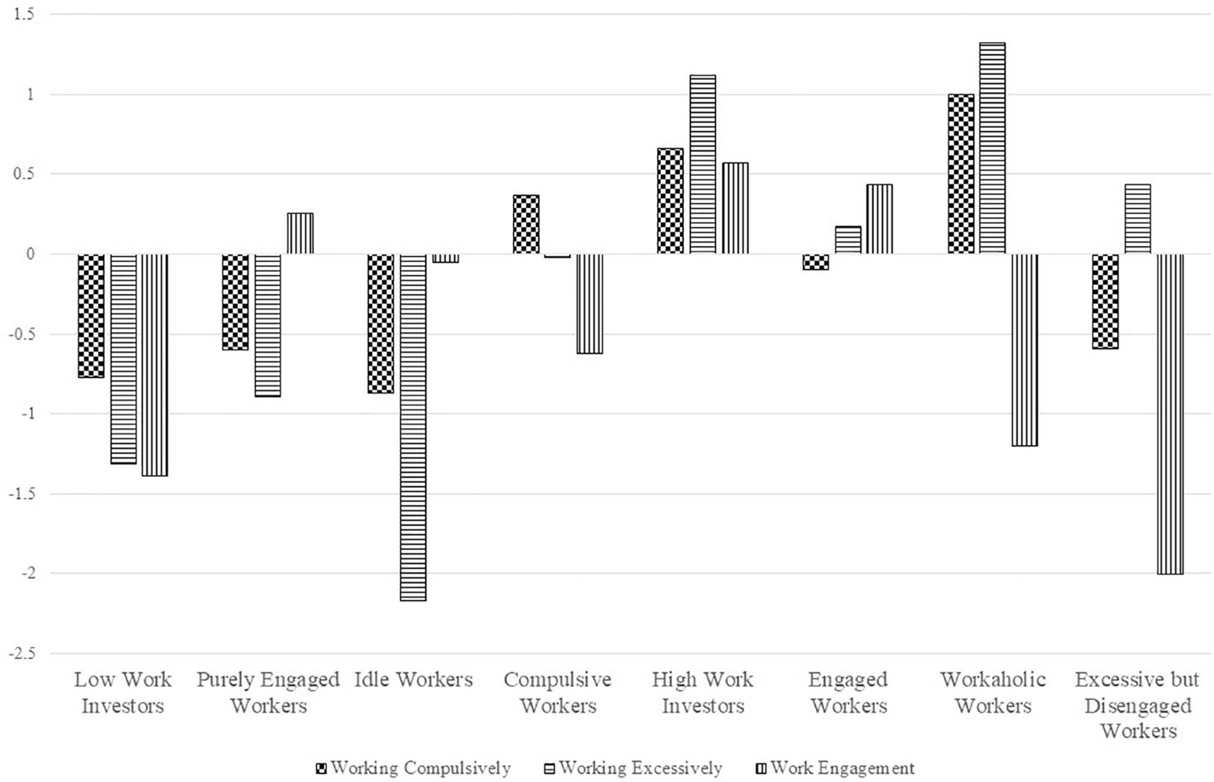

Fig. 1. Standardized means in the indicators working compulsively, working excessively, and work engagement for the eight-profiles solution (illustrative example).

seventh group was small (n = 28, 3%) and showed the overall highest values in working compulsively and working excessively, but low values in work engagement. We named this the *workaholic workers* group. Finally, the eighth group was characterized by below-average values in working compulsively, above-average values in working excessively, and the lowest values in work engagement. We named it the *excessive but disengaged workers* group (n = 23, 3%).

7.2.2. Criterion-related validity evidence: group differences in outcomes

We used the BCH-procedure in *M*Plus to compare differences across groups in the continuous outcome variables. This procedure conducts Wald tests to compare the mean scores of the outcomes across groups, and was found to offer robust results even for non-normal distributed variables (Bakk & Vermunt, 2016).[4] Fig. 2 shows the standardized values (below and above the mean) of the outcome variables separated by profile membership.

Regarding the negatively connoted outcome, the workaholic workers were those experiencing the highest burnout (with significant differences to all, with the exception of the compulsive workers), followed by the compulsive workers, the low work investors, and the excessive but disengaged workers (supporting Hypothesis 2). Low burnout was experienced by the purely engaged workers, the idle workers, and the engaged workers (supporting Hypothesis 3). The high work investors showed an intermediate level of burnout that differed to the levels experienced by all other groups (supporting Hypothesis 4). Regarding the positively connoted outcome, groups reporting the highest perceived marketability were the purely engaged, the idle, and the engaged workers, as well as the high work investors. The engaged workers differed significantly in their perceived marketability from all the remaining four groups (supporting Hypothesis 3). The lowest values in perceived marketability were reported by the excessive but disengaged workers. Somewhat higher, but still having low values in perceived marketability characterized the compulsive workers, the low work investors, and the workaholic workers. Thereby, the excessive but disengaged and the compulsive workers differed significantly from all the four groups with high marketability (partly supporting Hypothesis 2). Moreover, the high work investors showed intermediate levels of perceived marketability (supporting Hypothesis 4). In sum, these findings largely support Hypotheses 2 to 4, and therefore can be seen as a criterion-related validity evidence of the derived profile solution.

[4] There exist several different methods for contrasting distal outcome variables within LPA analyses. We do not refer to all available methods here, but recommend Bakk and Vermunt (2016) and Lanza, Tan, and Bray (2013) for the interested reader seeking to discover the advantages and disadvantages of these different methods.

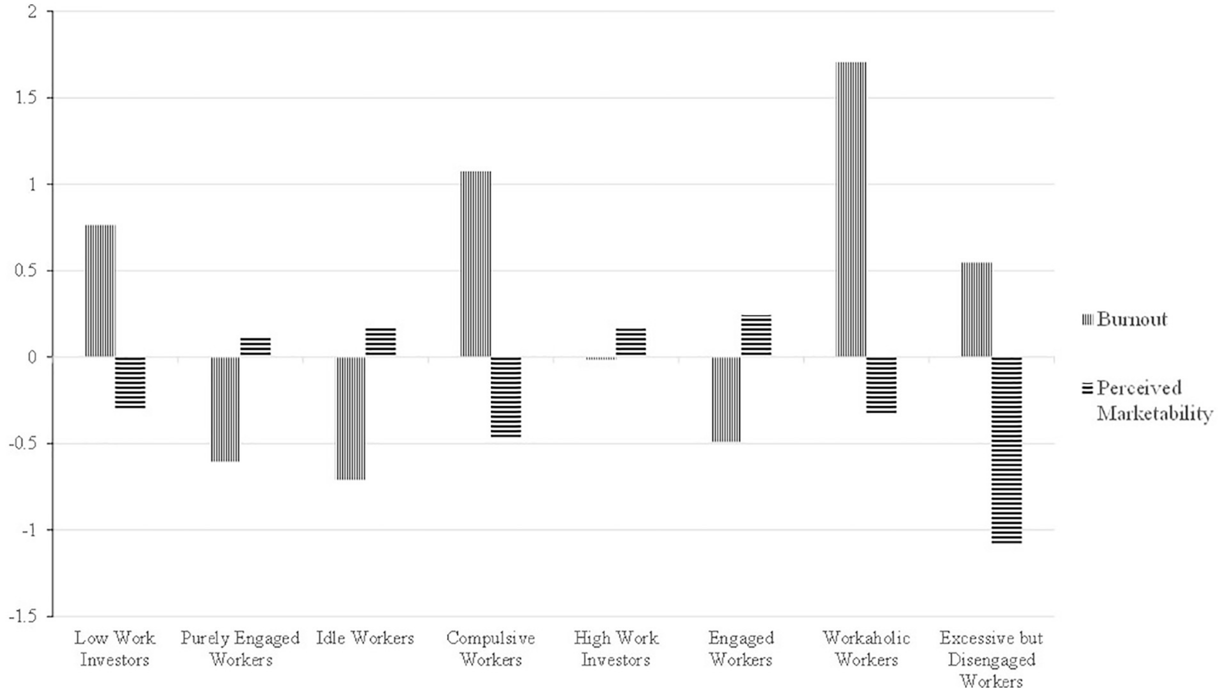

Fig. 2. *Z*-standardized values for the two outcomes of heavy work investment across the eight-profiles solution (illustrative example).

8. The future of LPA within vocational behavior research

8.1. Promising future research topics

Despite the fact that research using LPA has addressed a number of relevant topics for vocational behavior (see supplemental material), there are several research areas where LPA might provide additional important insights. For example, career success research assumes that objectively successful persons not necessarily need to be subjectively successful, and can even feel unsuccessful (Heslin, 2005). Thereby, different profiles of combinations of objective and subjective career success should emerge and be meaningfully related to different outcomes (Heslin, 2005). Another promising issue is that career actors can possess different types of protean and boundaryless career orientations (Briscoe & Hall, 2006). Past research theoretically assumed that four different components of these career orientations (i.e., self-directed career management, values-driven orientation, psychological mobility, and physical mobility) combine to several quantitatively and qualitatively different profiles with different names, and predictable for specific outcomes (Briscoe & Hall, 2006). Both topics (career success and career orientations) are highly central within vocational behavior research (Hall, Yip, & Doiron, 2018; Spurk, Hirschi, & Dries, 2019), and both topics have not been approached empirically with the LPA method. However, LPA methods could both theoretically and methodologically contribute to these important lines of vocational behavior research by examining if different configural profiles of successful/unsuccessful and protean/boundaryless career actors exist (and in which way and frequency). Such studies could also advance the understanding of how different constellations of success and career orientations relate to theoretically relevant predictors (e.g., personality traits, social support) and outcomes (e.g., life satisfaction, health).

In addition, although several studies examined job and career attitudes using LPA, not much was conducted on career behaviors. However, research has suggested that there are a large number of potential career self-management behaviors and career strategies (Lent & Brown, 2013), and it would be important to know if there are specific approaches of using career behaviors and strategies as represented in different profiles. For example, some people might use more internal organizational strategies, such as positioning or job crafting, whereas others engage in more external behaviors, such as career exploration or networking beyond the organization. Moreover, it would be interesting to know which variables (e.g., organizational support, labor market characteristics) predict the engagement in different constellations of behaviors and strategies, and if and how such constellations relate differently to outcomes (e.g., career satisfaction, promotions).

Another area that could benefit from research using an LPA perspective is investigating vocational attitudes and behaviors in relation to nonwork attitudes and behaviors. Because career development increasingly unfolds at a close intersection of work and home domains (Hirschi, Shockley, & Zacher, 2019), gaining a better understanding of how people simultaneously evaluate and engage in work and nonwork roles becomes an important issue. Research using LPA could, for example, investigate if there are different ways in which people are committed to the work role and other life roles, and thereby extend current research to different profiles of work-related commitment types (Meyer et al., 2015; Wombacher & Felfe, 2017). For example, some people might have more of a one-sided career commitment, others are strongly committed to nonwork roles, and still others show varying combinations of work and nonwork role commitments simultaneously. Such different commitment profiles might, in turn, differently relate to relevant outcomes, such as career success, nonwork satisfaction, work–life balance, or life satisfaction.

Although some studies investigated personality profiles and their relationships to vocational behavior outcomes, most of these studies focused on perfectionism. However, there might be other personality profiles that are based on different indicators that might be relevant for vocational behavior. For instance, constellations of stable traits related to positive psychological capital, such as hope or optimism (Luthans, Avolio, Avey, & Norman, 2007), might be one area of future research.

Another promising avenue for future research could be to take a categorical latent variable model approach to career counseling interventions based on LPA. Indeed, we identified only one study that included LPA indicators directly related to career counseling issues (Choi et al., 2015). Therefore, one promising area of future inquiry could be to examine career intervention variables as LPA indicators (e.g., counseling characteristics or intervention types), or as predictors or outcomes of other profiles (e.g., profiles of career adaptability or career-indecision as predictors of seeking different types of counseling). Related to counseling issues, future research might also more explicitly investigate the research question of profile prevalence to identify specific groups that might be in need of specific counseling approaches. For example, the findings that a small number of employees show a *true* burnout profile (Moeller et al., 2018) or a *true* workaholism profile (see illustrative example) provide practical insight for career counseling and human resource management focusing on such groups.

Finally, most research to date is cross-sectional, and takes a static view of LPA. However, studies could take a lifespan perspective to better understand dynamics and lifelong career development (Wang & Wanberg, 2017), including how constellations of variables change from early to late career. Such research could examine if the substantive nature of profiles changes across time, and apply latent transition analysis to examine how individuals transition from one profile to another over time, and which factors might explain such shifts (Collins & Lanza, 2013). For example, Kam, Morin, Meyer, and Topolnytsky (2016) examined how employees transition between different commitment profiles over eight months and found that changes in trustworthiness of management were related to shifts between commitment profiles.

8.2. Methodological considerations and reporting recommendations

Regarding the frequencies from Table 1, future research should more frequently apply either a validation based on latent class prediction or a replication of the profile solution within another sample. One possibility of doing this might be to collect data with the double sample size, as recommended above, and then conduct a random split, with the aim to replicate the LPA solution in the second random sample half. A replication of the same number and types of profiles across multiple samples would also be important for guarding against potential overinterpretation of spurious profiles. A related issue is that most of the studies (see Table 1) have been conducted within the United States and Europe. Future research might take the opportunity to replicate LPA profiles within non-Western cultures.

We also observed that several studies did not report raw data distributions, outliers, estimation problems, out-of-bound values, local maxima, random starts, missing value types or patterns, or tests of large enough sample sizes. Moreover, the provided methodological information about LPA was highly diverse across studies. Although this might be due to space restrictions in journals, a full reporting of the here reviewed issues is critical within LPA. Hence, even if researchers have conducted the respective tests with a positive outcome, it would be helpful to mention this to provide the reader with all necessary information. Related to this, we are not aware of LPA reporting standards similar to those that exist in several other methodological areas (Hinkin, 1995; Kepes, McDaniel, Brannick, & Banks, 2013). Hence, the development of such reporting standards, which might also be helpful for other categorical latent variable model methodologies, is a crucial issue for future research. By doing so, the results and interpretations of different studies would become more comparable within the future. The results of this review, and other reviews and methodological work in this area (e.g., Woo et al., 2018), might be helpful in this endeavor.

Further, although a substantial amount of studies applied several fit indices or a combination of fit indices and content decisions when reporting and interpreting the findings from LPA, researchers need to clearly identify what features would characterize meaningful "types", and evaluate whether the identified clusters or profiles exhibit those features. We already discussed some discrimination and theoretical consideration above. Some further possibilities are, for example, the taxometric method that specifies cluster separation and homogeneity as the key features for inferring the presence of types (Ruscio, Haslam, & Ruscio, 2013). Additionally, if clusters account for relatively little variance in variables, they are not likely to be particularly meaningful (McLachlan & Peel, 2000). Related to this issue, recent developments in confirmatory LPA allow a more concrete test of specific assumptions about LPA profile solutions (e.g., Finch & Bronk, 2011; Schmiege et al., 2018). Applying more of such LPA extensions in future research will provide more confidence regarding the meaningfulness of the derived LPA profiles.

8.3. Problems and pitfalls associated with LPA analyses

Despite the already mentioned advantages of LPA, there are also some associated problems and pitfalls. One of the most critical issues is related to the identification of "true" versus "spurious" profiles. Hence, the decision on the final number of profiles is also complex because identified profiles might be spurious due to methodological reasons, and thereby not representing true or meaningful profiles. Bauer and Curran (2004) showed that a second spurious profile can be detected when relying on several fit indices, even if the underlying data represents a single-profile solution. This can be specifically the case if (a) the within-class structural model is misspecified; (b) the data is non-normally distributed; or (c) profile indicators are non-linearly related with each other. Bauer and

Curran (2004) recommended applying a two-step procedure, where a series of unrestricted mixture models is compared with a hypothetically expected model. To address this issue, Muthén (2003) formulated a test that considers the higher-order moments (e.g., skewness and kurtosis) of the observed data. Todo and Usami (2016) also recommended calculating unstructured finite mixture models to deal with potential model misspecification. Guerra-Peña and Steinley (2016) provided some results on conditions where profiles might be spurious due to non-normality. Focusing on cross-sectional LPA applications, Peugh and Fan (2013) mentioned that the LPA assumptions of local independence of profile indicators and variance homogeneity can be one important reason for the misspecification of LPA models. In such cases, the number of profiles might get overestimated, and allowing for dependence or variance heterogeneity might lead to a more accurate performance of several fit indices (Peugh & Fan, 2013).

Another frequent problem is related to the discrimination of LPA indicators. High correlations among indicators can be due to the presence of a global construct as a source of the single LPA indicator (e.g., quality of work as global construct). If globality is not accounted for, the detection of qualitatively distinct profiles in LPA models is quite difficult because the globality tends to mask shape differences between profiles (Morin & Marsh, 2015). Possible solutions are the estimation of factor mixture models with continuous factors to account for globality, or the estimation of latent categorical variables from residual covariances (Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016; Morin & Marsh, 2015).

9. Summary and conclusion

In this article we provided a comprehensive review how LPA was treated within past vocational behavior research, provided non-technical guidelines about critical LPA issues, and illustrated these guidelines with an example from the heavy work investment literature. The review showed that vocational behavior research already relies on LPA methodology, and that some LPA issues are consequently reported and considered (e.g., mix of fit values), whereas others are not reported or considered that frequently (e.g., profile discrimination issues, replication of model solution). Based on these findings, we made several suggestions for how LPA might inform other areas of vocational behavior research (e.g., career management, work-nonwork issues), and how methodological issues can be advanced, or should be reported in future studies. We hope that this review, and the provided suggestions, contribute to conducting further LPA research within the future.

Declaration of competing interest

The authors whose names are listed on the title page certify that they have NO affilliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendix A. Supplementary material

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