Dries, N., Vantilborgh, T., Pepermans, R. (2012). The role of learning agility and career variety in the identification and development of high potential employees. Personnel Review, 41 (3), 340-358.

1. Introduction

The post-recession world organizations are operating in today is forcing them to rethink their human resource management (HRM) strategies (Right Management, 2010). A new economic landscape of constant change has emerged (Paauwe and Boselie, 2005). As marketplace complexity and dynamism increase, the importance of organizational agility moves to the forefront (Dyer and Shafer, 1999). In order for organizations to be adequately equipped for surviving and thriving under fast-changing market conditions, their human capital – the cornerstone of competitive advantage according to the contemporary strategic HRM literature (Wright *et al.*, 2001) – has to act accordingly. In other words, organizations need to focus their HRM systems on the selection, development, and deployment of a workforce that is willing and able to engage in continuous learning, i.e. a workforce high in learning agility (Lombardo and Eichinger, 2000; Paauwe and Boselie, 2005). This is especially true for high potential employees, that is, those employees who are considered most instrumental to the competitive advantage of their organizations (Lepak and Snell, 1999; Lombardo and Eichinger, 2003; Wright *et al.*, 2001). Recent empirical studies indicate, however, that the majority of organizations still rely heavily on performance data in their assessments of employee potential (Dries and Pepermans, 2008; Pepermans *et al.*, 2003). Furthermore, the academic literature reports very mixed findings with respect to the relative malleability of individual learning agility (e.g. Boyatzis *et al.*, 1996), so that it remains unclear whether organizations should focus more on its selection, or on its development (Briscoe and Hall, 1999).

Although there have been a handful of publications examining the relationships between learning agility and performance (Spreitzer *et al.*, 1997), being promoted (Eichinger and Lombardo, 2004a), and leadership effectiveness (Amagoh, 2009), there have not been any studies to date examining the added value of learning agility over job performance in assessments of employee potential. Furthermore, there have not been any studies examining the degree to which learning agility increases with career variety. The current study, conducted in a sample of seven best practice organizations in the field of high potential identification and development, examines the extent to which a measure of learning agility is able to predict being identified as a high potential above and beyond a baseline prediction by job performance. Furthermore, it investigates whether employee learning agility can be developed by organizations by building on the literature about career variety and employee adaptability (Karaevli and Hall, 2006).

Take in Figure 1 about here

1.1. High potentials as high learners

Although the identification and development of high potential employees (commonly referred to as talent management, see Dries, 2009) has been pinpointed by both management scholars and practitioners as one of the major challenges faced by the twenty-first century human resource function (e.g. Buckingham and Vosburgh, 2001), there has been very little theoretical development (Dries and Pepermans, 2008). The few conceptual papers that have been published on the topic (e.g. Collings and Mellahi, 2009; Lewis and Heckman, 2006) have borrowed from the literature on strategic HRM, the resource-based view (RBV), and differentiated HR architecture (see Lepak and Snell, 1999; Wright *et al.*, 2001).

There has been some debate about the added value of talent management over traditional HRM approaches, with some commentators labeling talent management as just another management fad (Chuai *et al.*, 2008). Others have argued, however, that talent management responds to the urgent need for more strategic diversification of HRM systems within organizations on the basis of the returns the performance of different employee groups generate on measures of strategic interest (Lepak and Snell, 1999). Like other organizational assets, employee skills can be classified as core or peripheral assets (Boudreau and Ramstad, 2005). High potentials, then, are those core employees whose skills are high in value and in uniqueness from the point of view of their particular employers (Lewis and Heckman, 2006). Consequently, in order for organizations to maintain an optimal level of agility (Dyer and Shafer, 2001), they need to make sure their high potential employees have high learning agility, i.e. a high "willingness and ability to learn new competencies in order to perform under first-time, tough, or different conditions" (Lombardo and Eichinger, 2000, p. 323).

In practice, however, individual job performance is still the cornerstone of high potential identification processes in many organizations (Pepermans *et al.*, 2003). Few would argue, however, that potential can be detected from current performance in an area the person already knows well (Lombardo and Eichinger, 2000). Studies on career derailment (e.g. McCall *et al.*, 1988), for instance, have found that numerous managers and executives derail because they tend to depend largely on the same skills which got them promoted in the first place rather than learning new ones. Hence, several authors have indicated that all high potentials are high performers, but not all high performers are high potentials (e.g. Corporate Leadership Council, 2005). In accordance with the literature (see De Meuse *et al.*, 2009), we hypothesize that individual learning agility, when linked to the high potential identification procedures of best practice organizations, will add substantially to the prediction of employee potential over and above the standard prediction by job performance (H_1). However, previous studies have indicated that organizations will typically wait two to three years before identifying new hires as high potentials, as they first want to see behavioral evidence for the person's underlying potential within the specific context of the organization (Dries and Pepermans, 2008; Pepermans *et al.*, 2003). This finding implies that actual on-the-job learning might serve as a mediator in the relationship between assessments of learning agility and being identified as a high potential or not (*H_2*).

> *H_1*. Assessments of learning agility predict whether an employee is identified as a high potential (or not) above and beyond the baseline prediction by job performance.
>
> *H_2*. The relationship between learning agility and being identified as a high potential (or not) is mediated by assessments of actual on-the-job learning.

1.2. Career variety and employee adaptability

In their seminal paper on career variety – i.e. "the diversity in an individual's functional area and institutional context experiences accumulated over time" (p. 360) – Karaevli and Hall (2006) argue that employee adaptability (a construct very similar to learning agility) develops from career variety over the span of a person's career. In other words, the authors assert that learning agility can be increased over time through exposure to varied career experiences. This is a very interesting avenue for further research as it implies that HRM interventions (e.g. job rotation, international assignments) can influence employee learning agility.

Karaevli and Hall's (2006) argumentation is that people who have spent most of their career within one single organizational or industry setting have developed a limited knowledge and skills base, and are more likely to engage in a limited search for information in the face of challenge, compared to employees with more varied experiences. Having a variety of experiences seems to be necessary for people to be able to extract some general principles or lessons from these experiences, and transfer previous learning to a novel situation (Spreitzer *et al.*, 1997). Consequently, we hypothesize that employees who have had more varied careers will score higher on assessments of learning agility (*H_3*).

> *H_3*. Career variety is associated positively with learning agility.

2. Methods

2.1. Procedure

The current study was part of a larger Belgian research project on the identification and development of high potentials. Data for the project was collected from a sample of best practice organizations in the field of talent management, as identified by a major consulting firm. The intention of the project was to distill valuable lessons about talent management for all organizations interested in optimization of their talent management policies based on data collected from best practice organizations. For this specific study we obtained the participation of seven organizations spanning four different industries: financial consulting (41% of respondents), distribution (35%), ICT (14%) and telecom (10%). The organizations participating in the study did not use ratings of learning agility to assess employee potential, at least not in any formal sense. Rather, a measure of learning agility (i.e. the Choices, see further down) was used by us for validation against their high potential lists – cross-checking existing high potential lists is one of the major applications of the measure (De Meuse *et al.*, 2009).

We conducted a survey study with a case-control design (see Sulitzeanu-Kenan, 2007). Employees identified as high potentials over the course of the past year represented the cases (i.e. the subsample demonstrating the outcome of interest in the study); the control group was composed of a matched subsample of non-high potentials. Within each participating organization, the case group was carefully selected by our contact person within the HR department to be representative for the organization's high potential population. Subsequently, each case group was matched with a control group of non-high potentials within the organization exhibiting a similar distribution in terms of gender, age and work experience.

Several psychometric studies have revealed that direct supervisors are the most accurate raters of employee learning agility – accurate in the sense that their ratings are good predictors of future performance and advancement, and relatively unbiased by friendly feelings toward the ratee (Atkins and Wood, 2002). What is more, Lombardo and Eichinger (2004b) discovered that the optimal duration of the working relationship between raters and ratees is around three years (i.e. long enough to get past first impressions, but not so long as to foster favorable generalizations). Based on these guidelines, we asked our HR contacts within the participating organizations to assign suitable raters to their preselected subsamples of ratees. Each ratee (either from the case group or the control group) was assigned one rater. No rater was assigned multiple ratees as we wanted to avoid comparisons between ratees, which might affect the ratings. All raters were direct supervisors to the ratees; the average duration of the working relationship between raters and ratees was 4.84 years (sd = 4.05). When raters indicated that they were not in a position to adequately assess the learning agility of their assigned ratee, that particular rater-ratee dyad was excluded from participation in the study. The participating supervisors were not informed about the inclusion of the high potential and career variety variable in the study prior to debriefing in order to reduce the risk of common method variance between these (factual) variables and the supervisor-rated variables.

2.2. Sample demographics

Raters (supervisors). Raters were 63 supervisors, each completing an online survey about their assigned ratee. Of the raters, 51 (81%) were men and 12 (19%) were women. Around half of them were middle managers (n = 36; 57%); 10 were line managers (16%), 9 were senior managers (14%) and 8 were executives (13%). Their average age was 43.83 (sd = 7.27). On average, the raters' tenure with their current organization was 17.77 years (sd = 15.87).

Ratees (direct reports). As for the ratees, 32 had been identified as high potentials during the year prior to the data collection and 31 had not been identified as such. Of the high potentials, 22 (69%) were men and 10 (31%) were women. Their average age was 36.59 (*sd* = 6.38). The majority of them had obtained either a university degree (*n* = 16; 50%) or a college degree (*n* = 14; 44%). On average, they had 13.53 years of work experience (*sd* = 6.94). Of the high potential ratees, 6 were in functions at a non-managerial level (19%); 7 were line managers (22%); 12 were middle managers (37%); 6 were senior managers (19%); and 1 was an executive (3%).

Of the non-high potentials, 18 (58%) were men and 13 (42%) were women. Their average age was 33.45 (*sd* = 6.44). The majority of them had obtained a college degree (*n* = 19; 61%); 6 obtained a university degree (19%). On average, they had 11.48 years of work experience (*sd* = 7.14). The majority of the non-high potential ratees were in functions at a non-managerial level (*n* = 23; 74%); 4 were line managers (13%); 3 were middle managers (10%); and 1 was a senior manager (3%).

2.3. Study variables

Both factual data (i.e. archival data provided by the HR departments of the participating organizations) and supervisor-rated data were collected. Raters were instructed to fill out the survey about their assigned ratee with the past year in mind. We added this specific timeframe in order to decrease the likelihood of reverse causality in our data.

2.3.1. Factual variables

Identification as high potential. Our HR contacts within each participating organization indicated for each of their ratees whether he or she had been identified as a high potential over the course of the past year (1) or not (0).

Career variety. Our HR contacts indicated for each of their ratees for how many different organizations they had worked during their entire career (i.e. institutional variety), and across how many different job domains (i.e. functional variety) (see Karaevli and Hall, 2006).

2.3.2. Supervisor-rated variables

Learning agility. In order to assess learning agility we used the Choices instrument, which was developed through a series of studies conducted by the Center for Creative Leadership (see Lombardo and Eichinger, 2000) and was designed specifically as a tool to assist organizations in their high potential identification processes. Several validation studies (e.g. Lombardo and Eichinger, 2003) demonstrated that the measure has four factors: mental agility (i.e. being attracted to new ideas and complexity, and being a quick thinker), people agility (i.e. actively searching for feedback and being open to diverse people and ideas), change agility (i.e. taking part in change and optimization processes), and results agility (i.e. delivering results even under first-time or difficult circumstances). Example items are: “Is able to see relationships between issues others do not see as related” and “Is creative and innovative”. Each item was rated on a 5-point Likert scale ranging from “1. Not at all like this” to “5. The clearest example of this”. For each item, there was also the option of answering “I don’t know/cannot give a valid appraisal”. Cronbach’s alphas were very high across the overall data set (.98 for the total score, .96 for mental agility, .95 for people agility and .92 for change agility and results agility) indicating satisfactory internal consistency. Tables 1 and 2 report the Cronbach’s alphas across the two subsamples (i.e. high potentials versus non-high potentials).

On-the-job learning. On-the-job learning was measured using the two items developed by Spreitzer *et al*. (1997). The authors identified two different dimensions of on-the-job learning: job content learning (i.e. “Relative to other people you have worked with, how effectively has this person learnt new technical, functional, service, or customer information?") and behavioral skill learning (i.e. "Relative to other people you have worked with, how effectively has this person learnt new behavioral skills – that is, new ways of interacting effectively with people in getting the job done?"). Both items were scored on a 5-point Likert scale ranging from "1. Not at all effectively" to "5. Very effectively".

Job performance. Job performance was measured by one single item, i.e. "During the most recent appraisal period, this person's job performance was rated as…". Response categories were: "Does not reach the expected level", "Reaches the expected level to some extent", "Reaches the expected level" and "Exceeds the expected level" (as in Fields, 2002). The supervisors were instructed to go back to their performance appraisal reports to look up this information, rather than reply top-of-mind. We added this instruction so as to decrease the potential effects of common method variance on our analyses.

3. Results

Tables 1 and 2 provide an overview of the means, standard deviations and intercorrelations of the study variables across the two subsamples.

Table 1. Means, standard deviations and intercorrelations for the case group ($n_{\text{high potentials}} = 32$).

	m	*sd*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Learning agility (total) [b]	4.11	.39	(.95)												
2. Mental agility [b]	3.73	.31	.80**	(.87)											
3. People agility [b]	3.54	.39	.68**	.65**	(.91)										
4. Change agility [b]	4.55	.51	.92**	.68**	.46**	(.76)									
5. Results agility [b]	4.63	.66	.88**	.51**	.35	.81**	(.78)								
6. Age [d]	36.59	6.38	.38*	.04	.18	.31	.54**	--							
7. Work experience [d]	13.53	6.94	.43*	.12	.27	.36*	.53**	.96**	--						
8. Educational level [c]	9.41	1.04	.01	-.06	-.22	.10	.11	-.13	-.14	--					
9. Institutional career variety [b]	2.03	.86	.37*	.18	.19	.38*	.37*	.24	.28	-.12	--				
10. Functional career variety [a]	3.03	.82	.36*	.00	.25	.37*	.43*	.49**	.49**	-.17	.41*	--			
11. Job content on-the-job learning [b]	4.31	.47	.06	.20	-.19	.15	.04	-.33	-.32	.13	.06	-.11	--		
12. Behavioral skill on-the-job learning [b]	3.84	.52	.35*	.32	.46**	.38*	.11	-.16	-.13	.00	.16	.01	.34	--	
13. Job performance [b]	4.03	.60	.35	.26	.34	.35*	.23	-.11	-.02	.08	-.00	-.00	.43*	.44*	--

Notes. Coefficient alphas are on the main diagonal.
[a] 4-point scale, [b] 5-point scale, [c] 11-point scale, [d] open-ended item; for each scale, we used the original format as proposed by its developers.
* p <.005; ** p <.001.

Table 2. Means, standard deviations and intercorrelations for the control group ($n_{\text{non-high potentials}} = 31$).

	m	*sd*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Learning agility (total) [b]	3.37	.66	(.98)												
2. Mental agility [b]	2.97	.65	.95**	(.96)											
3. People agility [b]	2.99	.65	.92**	.85**	(.96)										
4. Change agility [b]	3.76	.70	.96**	.91**	.84**	(.91)									
5. Results agility [b]	3.76	.81	.93**	.83**	.78**	.84**	(.92)								
6. Age [d]	33.45	6.44	-.52**	-.45*	-.66**	-.51**	-.36*	--							
7. Work experience [d]	11.48	7.14	-.50**	-.45*	-.64**	-.47**	-.37*	.95**	--						
8. Educational level [c]	8.68	1.28	.43*	.47**	.40*	.40*	.35	-.43*	-.46*	--					
9. Institutional career variety [b]	1.77	.81	.10	.03	.12	.05	.15	.22	.35	-.27	--				
10. Functional career variety [a]	2.48	.80	-.00	-.03	-.12	.01	.10	.08	.08	-.01		--			
11. Job content on-the-job learning [b]	3.58	.72	.68**	.75**	.58**	.60**	.65**	-.36*	-.43*	.47**	-.05	.02	--		
12. Behavioral skill on-the-job learning [b]	3.42	.77	.51**	.49**	.61**	.43*	.40*	-.65**	-.63**	.28	-.00	.15	.57**	--	
13. Job performance [b]	3.48	.77	.59**	.50**	.68**	.49**	.55**	-.71**	-.72**	.30	-.20	.21	.56**	.83**	--

Notes. Coefficient alphas are on the main diagonal.
[a] 4-point scale, [b] 5-point scale, [c] 11-point scale, [d] open-ended item; for each scale, we used the original format as proposed by its developers.
* $p < .005$; ** $p < .001$.

In order to assess the relative impact of job performance rating and learning agility on being identified as a high potential or not (H_1), we performed hierarchical logistic regression analysis with bootstrapping in *PASW* (v18). Job performance rating was added to the model in step one; learning agility was added in step two. The step one model proved statistically significant ($\chi^2(1, N = 63) = 9.60, p < .01$), indicating that the model was able to separate high potentials from non-high potentials based on their job performance ratings. The model explained between 14.1% (Cox and Snell R^2) and 18.9% (Nagelkerke R^2) of variance, and correctly classified 66.7% of ratees. Upon adding learning agility in step two, the model still proved significant ($\chi^2(2, N = 63) = 26.63, p < .001$). Moreover, adding learning agility significantly improved the model ($\Delta\chi^2(1, N = 63) = 17.03, p < .001$), and increased explained variance to 34.5% (Cox and Snell R^2) and 46% (Nagelkerke R^2), respectively. This model correctly classified 77.8% of ratees. As is shown in Table 3, although job performance made a unique significant contribution in the step one model, its contribution became insignificant once learning agility was added to the model in step two. In the step two model, learning agility is the only significant contributor with an odds ratio of 18.17, indicating that ratees high in learning agility were over 18 times more likely to be identified as high potentials. In sum, our findings support H_1.

Table 3. Hierarchical logistic regression predicting the likelihood of being identified as a high potential.

							95% BCa CI	
	B	S.E.	Wald	*df*	*p*	Odds ratio	Lower	Upper
Step 1.								
Job performance	1.21	.44	7.63	1	.006	3.35	.36	2.75
Step 2.								
Job performance	.21	.54	.15	1	.699	1.23	-1.02	1.47
Learning agility	2.90	.89	10.70	1	.001	18.17	1.15	10.16

Notes. $N = 63$; 10,000 bootstraps used.

In order to test H_2, we ran a logistic mediation analysis in *Mplus* to separate direct from indirect effects of learning agility on being identified as a high potential or not. Job content learning and behavioral skill learning, the two dimensions of on-the-job learning (Spreitzer *et al.*, 1997), were included as mediators. The technique used allowed for multiple mediators to be tested simultaneously based on the product-of-coefficients approach, while violations of multivariate normality were countered by bootstrapping. After performing 10,000 bootstraps, we constructed confidence intervals (CI) for each parameter and checked whether zero was contained in the interval, which would indicate non-significance. Figure 2 displays the path diagram. Results indicated that the total indirect effect – through both mediators – was significant ($\beta = .42$, $p < .05$, 95% CI: .10 to .84). More specifically, the indirect effect through job content learning was positive and significant ($\beta = .48$, $p < .01$, 95% CI: .21 to .92), while the indirect effect through behavioral skill learning was non-significant ($\beta = -.05$, $p = .68$, 95% CI: -.34 to .17). Finally, the direct effect of learning agility on identification as a high potential was only marginally significant ($\beta = .52$, $p = .11$, 90% CI: .03 to 1.1). We thus found only partial support for H_2.

Take in Figure 2 about here

Hierarchical multiple regression analysis was conducted to assess the degree to which career variety predicts learning agility (H_3). Although we did not posit formal hypotheses in relation to age, educational level and work experience (due to inconsistent findings in the literature, e.g. Boyatzis *et al.*, 1996), we did add these variables in our regression model in order to more fully assess the relative malleability of the learning agility construct. As correlation patterns between the case group (Table 1) and the control group (Table 2) differed substantially, we added the interaction term of each independent variable with the high potential dummy (0/1) to the model in a second step (see Table 4). Independent variables were mean-centered prior to computing the interaction terms. Collinearity statistics indicated that the multiple correlation between age and work experience ($r = .95$, $p < .001$) was unacceptably high (Tolerance: .09; Variance inflation factor: 11.40). We decided to remove age from the model as the work experience variable relates more explicitly to the work domain. H_3 was supported (see Table 4).

Table 4. Hierarchical multiple regression predicting learning agility.

	Step 1.		*Step 2.*	
	β	95% BCa CI	*β*	95% BCa CI
Educational level	.22**	[.08 to .39]	.19*	[.07 to .41]
Institutional career variety	.23*	[.05 to .40]	.24*	[.07 to .43]
Functional career variety	.21*	[.03 to .37]	.18*	[-.01 to .36]
Work experience	-.01	[-.04 to .01]	-.01	[-.04 to .02]
Educational level * Identification as high potential			-.11	[-.39 to .47]
Institutional career variety * Identification as high potential			-.25	[-.65 to .12]
Functional career variety * Identification as high potential			-.03	[-.39 to .45]
Work experience * Identification as high potential			.06*	[.004 to .11]
R^2	.31		.41	
Adjusted R^2	.27		.32	
F	6.58**		4.72**	

Notes. $N = 63$; * $p <.005$; ** $p <.001$; 10,000 bootstraps were used; bias-corrected and accelerated confidence intervals are provided. If 0 is contained within the interval the effect is non-significant.

In the first step, the four predictors together explained 31.2% of the total variance in learning agility. However, as our sample size was relatively small, we must report the adjusted R^2 here, which was 26.5%. Three of the four predictors (educational level, institutional variety and functional variety) proved significant; work experience did not. In the second step, where the four interaction terms were added, the explained variance in learning agility increased to 41.2%. However, the change in explained variance, by itself, was non-significant ($F(4,58) = 2.28$, $p = .07$). Considering each interaction term separately, we see that only the interaction between work experience and being identified as a high potential or not proved significant.

4. Discussion

The current study responds to urgent calls in the literature for more empirical research on the identification and development of high potentials (e.g. Collings and Mellahi, 2009; Lewis and Heckman, 2006). A survey study was conducted in seven best practice organizations in the field of talent management. By cross-checking their existing high potential lists (as suggested by De Meuse *et al.*, 2009), we aimed to demonstrate the added value of incorporating a measure of learning agility in assessments of employee potential in any organization. Furthermore, we wanted to examine whether learning agility can be developed by HRM interventions aimed at increasing employee career variety. Our hypotheses were largely supported.

As regards our first hypothesis, results indicated that learning agility is, indeed, a strong predictor of being identified as a high potential or not. Learning agility even proved to be a better predictor than job performance, which is still the key determinant of high potential identification processes in many organizations today – despite the many objections raised in the management literature (Lombardo and Eichinger, 2000; Pepermans *et al.*, 2003). Upon adding learning agility to our hierarchical logistic regression model, job performance was no longer a significant predictor of being identified as a high potential or not. Looking at the odds ratios, we see that high performers are three times more likely to be identified as high potentials than employees with a lower performance; being high in learning agility, however, increases a person's likelihood of being identified as a high potential by eighteen. Based on these findings, we conclude that although high performance may be a precondition to being identified as a high potential, learning agility is an overriding criterion for separating high potentials from non-high potentials. Our findings seem to correspond to earlier findings in the literature. A report published by the Corporate Leadership Council (2005), for instance, affirmed that 71% of high performers were not high potentials, whereas 93% of high potentials were also high performers. It is extremely important that organizations take findings such as these to heart in designing their high potential identification procedures, if they want them to impact positively on organizational performance (Briscoe and Hall, 1999).

Considering the results in relation to our second hypothesis, however, we must apply some nuance to the above findings. In the mediation analyses we ran to test the indirect effect of learning agility on identification as a high potential through on-the-job learning, we found that the direct effect of learning agility was only marginally significant. Furthermore, only the indirect effect through job content learning (relating mostly to technical skills) was significant, while behavioral skill learning (relating mostly to interpersonal skills) was not found to be a significant mediator. In other words, organizations appear to rely mostly on observable, on-the-job learning behavior involving the development of technical skills in their assessments of employee potential. It is commonly reported that organizations are hesitant to ground their assessments of employee potential in intangible measures (Pepermans *et al.*, 2003), and that they want to see behavioral evidence for assumed underlying employee qualities over a certain amount of time (typically two to three years) before they are willing to identify him or her as a high potential (Dries and Pepermans, 2008). As the learning agility measure we used (Lombardo and Eichinger, 2003) operationalizes learning agility as an underlying personal characteristic, and the on-the-job learning measure we used (Spreitzer *et al.*, 1997) was designed to probe actual learning behavior, the above findings were thus largely in line with expectations. However, we had expected that on-the-job learning behavior involving the development of interpersonal skills would play a role in predictions of employee potential as well, especially since Lombardo and Eichinger (2000) asserted that this type of learning, specifically, is much more characteristic of high potentials than it is of non-high potentials. Although not finding this effect was unexpected, it does correspond to one of the results of a recent study on high potential identification and emotional intelligence (Dries & Pepermans, 2007) that found that in the early stages of a high potential's career, continuous high performance is emphasized to such an extent by his or her employing organization that the development of interpersonal skills tends to suffer. Organizations need to beware of these dynamics, as it may lead to attrition from the high potential program; not developing better personal skills is the main predictor of career derailment during midcareer (McCall *et al.*, 1988).

Our third hypothesis, on the association between career variety and learning agility, was fully supported by our data. Although management discourse (which can have far-stretching effects on organizational practice) tends to focus on the negative side of career variety (i.e. "not being focused", "being a job hopper"), our findings indicated that people who had had more varied careers (both in terms of the number of organizations they had worked for and the number of job domains they had experience with) were also higher in learning agility. This finding corresponds to the propositions developed by Karaevli and Hall (2006), in their seminal paper on career variety. We also found that educational level was positively related to learning agility, and that work experience was associated positively with learning agility for high potentials, but not for non-high potentials. This interaction effect is possibly caused by the higher average functional variety in more experienced high potentials as compared to the control group of non-high potentials (see Tables 1 and 2) – in other words, by the fact that the high potentials have encountered a larger variety of experiences throughout recent years. Due to the cross-sectional nature of our data, however, we must also consider reverse causality hypotheses. For instance, it is possible that people higher in learning agility are more likely to aspire to more varied careers or a higher level of education. This is a matter, however, that only a meticulously designed longitudinal study can resolve.

4.1. Limitations

Due to limitations in time and resources, a longitudinal or prospective design was not feasible. Instead, we used a case-control design to test the study hypotheses. The most obvious limitation of this type of design is that it is not particularly well suited for demonstrating causal effects (case-control designs are mainly used to estimate odds ratios). It does, however, have some advantages over regular cross-sectional and even longitudinal designs. As the prevalence of the outcome of interest is typically very low in case-control studies (studies estimate that only between 1 and 5% of employees are identified as high potentials by their organizations, see Dries, 2009), random sampling from a population would yield too few instances of the outcome to allow for reliable analysis, and lead to major oversampling of the control group (Sulitzeanu-Kenan, 2007). Conversely, applying a longitudinal design to our research questions would have meant waiting for the event (i.e. being identified as a high potential) to happen, which would have been quite inefficient. Furthermore, we only used data about ratees who had been identified as high potentials over the course of the past year and instructed supervisors to rate them with the past year in mind. This way, we were able to significantly reduce the odds of reverse causality effects in our data (the odds that being identified as a high potential increased a person's on-the-job learning, for instance).

Another possible limitation caused by the non-longitudinal nature of the data is common method variance. Several interventions were introduced in the design, however, in order to prevent common method bias from occurring. First of all, we made sure not to collect only supervisor-rated data. Two of the variables in our research model (i.e. being identified as a high potential or not, and career variety) were factual, i.e. generated from archival data obtained from the HR departments of the participating organizations. Second, the inclusion of these factual variables in the study design was not disclosed to raters prior to debriefing, which reduced the odds of common method variance between the high potential variable and the learning agility variable, for instance. Third, in order to avoid common method variance between learning agility and job performance, we instructed respondents to base their job performance ratings on recent performance appraisal reports rather than on their opinion at the time of survey administration. We could not, however, exclude the possible effects of rater Halo bias on our findings (Lombardo and Eichinger, 2000). Fourth, for each scale incorporated in the survey, we used the original response format. Consequently, the number and labels of response anchors were very different across the survey, which according to Schwarz *et al.* (2008) decreases the odds of common method variance occurring. Finally, in our design raters did not have to disclose their scores to ratees after completion of the survey. Earlier research (e.g. Eichinger and Lombardo, 2004b) has indicated that assessments of learning agility are much less biased when raters are not required to report back to ratees.

A final limitation was posed by the relatively small sample size (*N* = 63) of our study. We were not able to conduct multi-level analyses as the data per organization was too limited; furthermore, a small sample size generally affects a study's power. Post-hoc power analyses revealed that the power for all our analyses was around .80, which is satisfactory. Nonetheless, it is possible that some of the effects we did not find do actually occur in the population (e.g. the effect of behavioral skill learning on being identified as a high potential), and that we underestimated the effect sizes of the effects we did find (i.e. type II error). The fact remains, however, that the current study represents one of the first serious attempts to collect empirical data about employees identified as high potentials. Very little research has been done in this population as it concerns a group that is difficult to reach, and very much shielded from research by their employing organizations (Dries, 2009). Furthermore, the case groups for our study were selected to be representative for the high potential populations within their organizations, and carefully matched to control groups. Although this was not a perfect solution for the issues associated with small sample sizes, it did allow us to control for many potential confounding variables.

4.2. Avenues for further research

The most promising avenues for further research on learning agility and career variety demand the use of longitudinal designs. By studying the career variety and learning agility of employees over time, causal inferences might be made about the malleability of learning agility, and about the processes leading up to the acquisition and enhancement of technical and interpersonal skills at work (Karaevli and Hall, 2006; Spreitzer *et al.*, 1997). Longitudinal data would also be required to demonstrate the link between high potential identification and development policies and individual and organizational performance at a later point. First of all, longitudinal studies linking assessment center data to performance or effectiveness criteria later on in a high potential's career would be an interesting way forward (Dries, 2009). Another suggestion is to do a longitudinal study of the factors leading to high potential career derailment, that is, those factors causing removal from the organization's high potential list or ineffective work behavior later on in the career (McCall *et al.*, 1988). Longitudinal research is also needed to expose potential conflicts between short- and long-term concerns in policies concerning the identification and development of high potentials. It appears that there is an inherent conflict between the need for performance in the short run and learning the competencies necessary for success in the long run – as is demonstrated by our finding that demonstrating technical skill learning predicts being identified as a high potential or not, but not interpersonal skill learning (Dries and Pepermans, 2007; Spreitzer *et al.*, 1997). Finally, longitudinal multi-level studies could examine the (indirect) effects of high potentials' learning agility on measures of organizational performance – i.e. financial outcomes (e.g. profits, sales, market share), organizational outcomes (e.g. productivity, quality, efficiency), and HR-related outcomes (e.g. employee satisfaction, commitment, and intention to quit) (Paauwe and Boselie, 2005).

4.2. Implications for practice

Briscoe and Hall (1999), in their study of 31 organizations engaged in talent management, found that they took an average of 4.1 years to revise their competency frameworks. This is far too slow to keep up with the fast-changing demographic and employee engagement trends characteristic of the post-recession economy (Right Management, 2010). Although organizations do acknowledge that developing employee learning agility is crucial due to the unpredictability of the end-state competencies that will be needed to cope with future business challenges (Dries, 2009), the question remains whether and how they, in fact, incorporate this factor into their daily activities and assessments.

The results of the current study, taken together with the results of previous studies (e.g. Lombardo and Eichinger, 2000; Spreitzer *et al.*, 1997) imply that it is in organizations' best interest to incorporate some form of learning agility assessment in their high potential identification and development processes. The literature clearly indicates that the relative value of "regular", end-state competencies in predicting employee potential is strongly dependent on the degree to which they will still be relevant several years after assessment, as well as on the degree to which they can be developed, and over what period of time (Briscoe and Hall, 1999). A suggestion is to use end-state competency assessments in performance appraisals, and learning agility assessments in high potential identification procedures. This might help organizations nominate better candidates, as it reduces the risk of Halo bias (De Meuse *et al.*, 2009). Educating managers about the difference between performance and potential is one of the applications of the Choices instrument (Eichinger and Lombardo, 2004a). Furthermore, using a quantifiable, objective tool such as the Choices to identify high potentials has some other benefits, as well. First of all, it increases the likelihood of identifying “diamonds in the rough”, i.e. atypical high potentials or high potentials that somehow have limited visibility with upper management. Second, it is likely to produce more positive employee attitudes about their organization’s talent management procedures, as it would increase perceived procedural justice and eliminate contention as to high potential selection being based mainly on management’s gut instincts (De Meuse *et al.*, 2009). As for accountability, Lombardo and Eichinger (1997) state that, although direct supervisors are the most accurate assessors of learning agility, the process should not be left up to them as they “just don’t have the time, the willingness, the skills, or the interest” (p. 143). They also advise against using self-assessments of learning agility in high potential identification processes, as high potentials tend to underrate themselves, whereas non-high potentials tend to overrate themselves. According to the authors, the HR department should take the lead in the process, whereas direct supervisors might be approached for the execution of some well-defined identification and assessment tasks.

Another implication for practice is that if organizations want to establish a workforce high in learning agility, introducing HRM interventions to increase their employees’ career variety might be the way forward. For instance, organizations can boost the degree of institutional variety within their workforce by deliberately hiring people who have worked for many different organizations over various industries, or by allocating their current employees to stretch assignments that span multiple organizations. Likewise, they might enhance their employees’ functional variety by assigning them to job rotation schemes or cross-departmental task forces (Karaevli and Hall, 2006). Furthermore, organizations need to become more aware of the fact that they themselves can create barriers to learning, even in their high potential programs. Being forced into a development track that moves either too fast or too slow, a lack of developmental opportunities, structures or support in the organization, and constraints in terms of time, space and budget have all been mentioned as barriers hindering the transfer from learning agility to on-the-job learning behavior in high potential development programs (Feild and Harris, 1993).

Finally, organizations need to make sure that not only the performance and the learning agility of their high potentials is high, but also their commitment. In order to achieve high commitment, organizations need to establish an employment relationship with their high potentials based on mutual benefit. Earlier publications on talent management (e.g. Dries & Pepermans, 2008) have outlined the following perceived benefits of being identified as a high potential: having high job security, advancing quicker than peers, having a more successful career in the traditional sense (i.e. pay and promotions), and receiving preferential treatment. Organizations need to keep these motivators in mind in the design of their talent management systems; if the achievements of high potentials are to result in sustained competitive advantage for their employing organizations, than these employees must be willing to stay where they are (Paauwe and Boselie, 2005).

5. References

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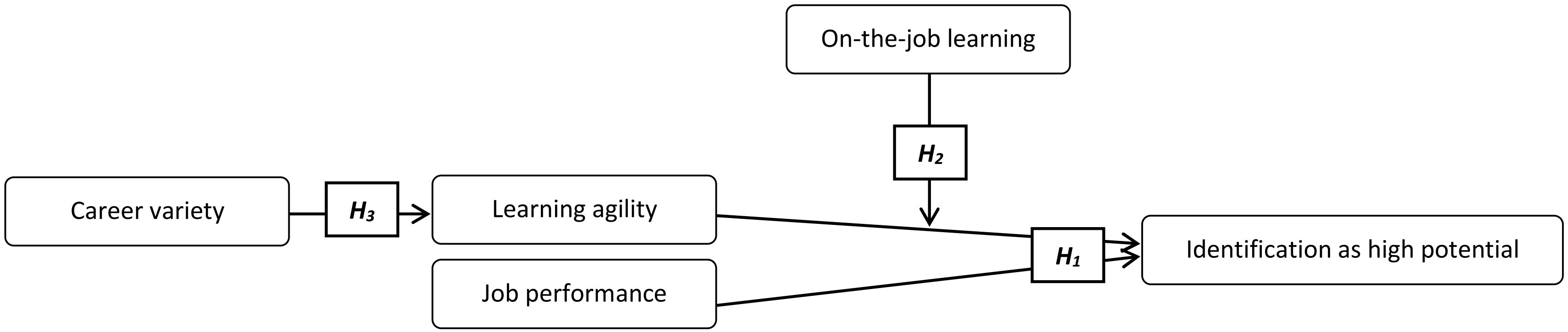
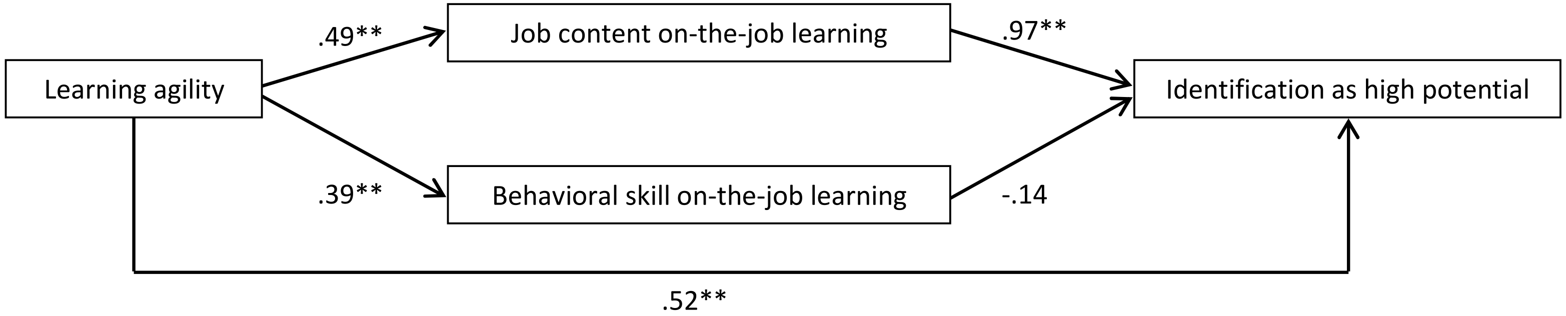


Figure 1. Research model.



Notes. ** p <.001; N = 63; 10,000 bootstraps used.

Figure 2. Path model of the direct and indirect effects of learning agility on being identified as a high potential or not.