



Managing academic performance by optimal resource allocation

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Abstract

In this paper, we develop and study a complex data-driven framework for human resource management enabling (i) academic talent recognition, (ii) researcher performance measurement, and (iii) renewable resource allocation maximizing the total output of a research unit. Suggested resource allocation guarantees the optimal output under strong economic assumptions: the agents are rational, collaborative and have no incentives to behave selfishly. In reality, however, agents often play strategically maximizing their own utilities, e.g., maximizing the resources assigned to them. This strategic behavior is typically mitigated by implementation of performance-driven or uniform resource allocation schemes. Next to the framework presentation, we address the cost of such mitigation.

Keywords Talent performance · Talent recognition · Performance monitoring · Resource allocation · Incentives · Strategic behavior

Introduction

Contemporary research on talent management addresses a large number of issues ranging from talent recognition, identification of contextual features necessary for talent development, employees' sensitivity to "talent" nomination, to creation of global pipelines to attract, develop, deploy and retain the talented employees within an organization (Bjorkman et al., 2013; Thunnissen & Van Arensbergen, 2015; Thunnissen, 2016; Collings et al., 2019). Shortage of talented employees and complexity of talent identification (Jooss et al., 2019) make the research on employee performance management utmost urgent (Cappelli & Keller, 2014; Collings et al., 2019). Employers and researchers believe that talented

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employees are earnest of success for an organization in general and for a structural unit in particular. To flourish the talents, organizations are ready to provide employees with additional opportunities and resources in hope of keeping them for further development within the organization.

At the same time, the problem of recognizing the talents who deserve to be endowed with scarce resources, such as unique education, promotions, extended authority and so on (Thunnissen, 2016; Swailes & Blackburn, 2016) is still lacking resolution and poorly presented among practitioners and scholars. Methodological results and prescriptive approaches to how the organization can recognize its talents and how to measure/manage their performance are also very limited. Moreover, we have not found much methodological literature on the influence of a scarce resource allocation on the employee performance in knowledge-intensive sectors, e.g., assignment of research assistants to academicians or software engineers to IT project managers.

In this paper, our goal is threefold. When developing a complex data-driven, though very intuitive, human resource management framework, first, we aim at modelling a talent recognition. Second, we want the model to be able to measure an employee performance over time and forecast the results of an employee's work. Last but not least, given the forecasts of the employee performance, we aim at resource allocation maximizing the total output of the organization for a given time horizon. Pursuing these goals, we model employee performance as an additive combination of three components: personal performance, resource-sensitive performance, and communication-sensitive performance. Moreover, we concentrate on performance of employees in knowledge-intensive areas with hardly any routine work responsibilities. We model the employee performance using fuzzy sets and learning curves (Heidary Dahooie & Ghezel Arsalan, 2013) and we optimize the resource allocation using tractable and intuitive methods.

Embedding in the current literature

Literature review on talent management reveals that the notion of talent is not universal (Tansley, 2011; Dries et al., 2011) and is formed by the set of contextual factors (Tansley et al., 2013; Vaiman et al., 2017). Searching for commonly accepted talent identification measures (Simonton, 2008; Nijs et al., 2014; Jooss et al., 2019; Lai & Ishizaka, 2020; Wiblen & McDonnell, 2020; Tyskbo, 2021), we came to a conclusion that all such measures can be operationalized and put into a simple and computable model based on three contextually transferable dimensions: performance, potential and performance dynamics (Sturman, 2007; Sonnentag & Frese, 2012; Minbashian & Luppino, 2014; Alessandri et al., 2015). Being context driven, the exact definitions and scales of these dimensions may differ across organizations (Gallardo-Gallardo et al., 2020). Despite recent intense progress of research on talent management, applied tool-kits for talent identification and performance/potential tracking are still underdeveloped.

One of the feasible approaches to performance/potential monitoring is presented in operations management and operations research literature, where researchers are dealing with staffing and personnel scheduling when optimizing some organization-wide output measure(s), see, e.g. (Campbell, 1999; Wu & Hou, 2010). In operations research, it is typically assumed that employees, like machines, have a certain level of performance and the tasks are routine operations specific for low-skilled personnel, laborers, workers of mass recruitment (Campbell, 1999; Shafer et al., 2001). In this case, sufficient taxonomy

of employee performance can be based on learning curves models, see e.g. Anzanello and Fogliatto (2011), where the authors analyze three main groups of learning curves in an application to employee performance: log-linear, hyperbolic and exponential. Providing insightful examples of models, the authors emphasize that the usage of learning curves as a tool of performance monitoring is possible mostly for the cases of repetitive routine tasks. Boh et al. (2007) point out the lack of research on applicability of learning curve models to the knowledge workers while they advocate the usage of learning curves for performance measurement of programming engineers. Regarding the learning curves for the employee performance modelling at individual, team and organizational levels, Boh et al. (2007) conclude that the learning curves might also be applied to the case of knowledge workers. Boh et al. (2007) highlight that, despite the significance of the achieved results, their research has limitations in terms of understanding how managers can leverage individual, team and organizational performance. The staffing and scheduling problems in operations research are often computationally intractable even in the simplest settings. To overcome the complexity, designers of decision support tools and professionals simplify and routinize the jobs/tasks in the problem descriptions (de Oliveira et al., 2018). This leads to intuitive and transparent mechanisms for decision making, but sub-optimal solutions to the practical problems.

Another research avenue to talent recognition and performance measurement is applying learning curve models to embrace the complexity of creativity and talent unfolding over time (Simonton, 1997; Howard, 2009, 2014, 2018; Weinberg & Galenson, 2019). In most of these papers, researchers develop life-long performance models rather than operational and controllable dynamic models. For instance, Simonton (1997) presents a talent performance model spanning the whole life cycle of a talent. Simonton (1997) constructs a learning curve reaching a peak at some point, stipulated by the specialty, and then declining. According to Simonton (1997), there is a predisposed level of creative potential which stipulates the exact shape of a particular curve. Another example of performance of highly intelligent professionals, such as chess talents, is discussed by Howard (2009, 2014). He found that in spite of frequent implementation of power law functions, see, e.g. (Argote, 1996; Kim et al., 2012; Glock & Jaber, 2014), there is no ubiquitous rules of how learning curves reflect performance scan. The power law functions best fit the group performance curves while the log functions describe individual performances better. It is also evident that under some assumptions and limitations the exponential and quadratic models are better fit.

These results suggest that implication of learning curves to such a complex construct as talent performance monitoring is possible. Although the authors advanced thoroughly on this path and elicited sets of traits of characters inherent to highly skilled people, we still have not found any mechanisms of how employers would be able to discern talents' potential and predict their performance in the context of organizations.

Turning to the subject of talent performance prediction, in order to develop a framework which helps an employer manage performance of talents over time, we should choose not only the type of learning curves best reflecting the performance dynamics, but also include those peculiarities of talent which give options to managers to leverage the performance of any employee, regardless whether she just start working for the organization or has been working for a long time. Elaborating such a framework, we depart from the premise of scarcity (i) of the resources allocated to the employees; and (ii) of data concerning the employees' potential and performance.

Trying to develop an intuitive toolkit based on the talent dimensions mentioned above, we elaborate a demarcation system of individual performance which contains three main

sets of variables. The sets are personal performance, which represents the results of a person's activities based on one's own abilities and skills; resource-sensitive performance, through which we examine how individual performance is altering over time depending on the quantity of resources allocated to the person; communication-sensitive performance which contributes to the individual performance from the position of information exchange between employees from the same work group or a department.

In our research, we consider employees of a particular organization as very important individuals who influence significantly the organization performance (Cappelli & Keller, 2014). Moreover we regard a dismissal as the last possible decision. Step-by-step, we complicate the problem by adding variables as possible managerial leverages. Nevertheless, we are trying to find an intuitive and implementable approach which can be used by managers, can help them recognize high potentials, and make decisions on optimal resource allocation.

Distinctive properties and essential ingredients of the performance model

Our aim is to develop a model of employee performance that is (i) simple and computable, (ii) dynamic, and (iii) intuitive. All literature in Sect. 2 address some of these three aspects but never all of them at once. A combination of all these features in a single model would give an opportunity for academicians to systematically analyse employee's behavior and organizational development, and for managers to implement and operationalize a performance boosting system based on the efficient resource allocation.

Throughout this paper we regard a generic employee of an organization as a *talent*. To integrate the literature findings into our model, we discuss three basic components of the individual performance of a talent stipulated above, which are:

- Personal (“*eigen*”) performance: Personal contribution of the talent (one's skills, competencies, previous experience, demonstrated potential by means of cognitive abilities), converted into result by one's personal efforts, see, e.g. (Motowidlo et al., 1997; Sturman, 2003; Sonnentag & Frese, 2012);
- Resource-sensitive performance: The result obtained by a certain quantity of investments (trainings, money, assistance, machines), see, e.g., (Baard et al., 2014; Niessen & Jimmieson, 2016);
- Communication-sensitive performance: The result added by or depreciated via the attitude of a talent to the allocation of investments see, e.g. (Tai et al., 2012) and her perception of fairness regarding this allocation, see, e.g. (Weiss & Merlo, 2020).

We assume that the talent's individual performance is the sum of personal, resource-sensitive and communication-sensitive performances. This approach to a talent does not prioritize any of the additive performance component upon the others; it does not insist on a narrow, field-specific understanding of a talent; it emphasizes the contextual approach to talent management and her individual performance; and it focuses on the team and organizational performance. In this setting, a typical task of a decision maker is to allocate resources and to manage the information flows in organization in such a way that the sum of individual performances of all talents in the team/organization over a given time horizon is maximized.

An illustrative example and notations

Consider the following, very intuitive and natural, example motivating and illustrating our research. In a West-European university, an academic lab consisting of seven professors (2 full, 2 associate, and 3 assistant professors) hires a new assistant professor. The output of the lab is measured in the (possibly weighted) number of publications. Consequently, performance of a professor is also measured in the number of her publications. In the forthcoming ten years, the lab has funding to maintain ten PhD positions a year. Here, each professor is seen as a *talent* and PhD students are seen as generic scarce *resources* adding to the productivity of professors. Without loss of generality, we assume that each professor can simultaneously accommodate at most 3 students in her projects.

Throughout the paper we use the following notation:

- Let n be the number of employees in the organization (professors in the lab), accounting also for new employees. Let $V = \{1, 2, \dots, n\}$.
- Let T be the employment horizon expressed in a number of days, months, quarters (in our example, years). Let $\mathcal{T} = \{1, 2, \dots, T\}$.
- For $i \in V$ and $t \in \mathcal{T}$, let Y_{it} denote the total output of the employee at term t of her employment (the number of publication in the illustrative example).
- Let p_{it} be the amount of resource (the number of PhD students) assigned to employee $i \in V$ in time $t \in \mathcal{T}$.
- Let p_{\max} be the maximum amount of resource that an employee can accommodate (e.g., three PhD students per professor). Clearly, $p_{it} \leq p_{\max}$ for all $i \in V$ and $t \in \mathcal{T}$. We refer to these inequalities as the *box constraints*.
- Let $P(t)$ be the total amount of resource available in time $t \in \mathcal{T}$ (in the example, the lab has ten positions available every year). Then, the resource constraint reads $\sum_{i=1}^n p_{it} \leq P(t)$ for all $t \in \mathcal{T}$. Further, we refer to these inequalities as the *budget* or *capacity* constraints.

Personal performance and aging effect

The first term of employee’s individual performance is her personal performance independent of the resource allocation and communication within and outside the organization. In the contemporary literature, personal performance is usually modelled by a learning curve which is monotonically increasing and asymptotically tends to a constant, i.e., a typical sigmoid. For instance, one of the ways to express such a learning curve is

$$A_i(t) = \alpha_{1i} \left(\frac{1 - e^{-\alpha_{2i}t}}{1 + e^{-\alpha_{3i}t}} \right), \quad i \in V, \tag{1}$$

for some positive real constants α_{1i} , α_{2i} and α_{3i} . Here and throughout the entire paper, all Greek letters denote parameters of the models. In our implementations, all these parameters are learned in the respective regressions. Also notice that the terms of employment are not necessarily synchronized, e.g., at the same time one employee can celebrate her 10th year in the organization while another one is just a fresh novice.

However, Simonton (1997) argues, and our data-set and common sense confirm it, that at some point in time, performance of an employee reaches its peak and then starts

decreasing as there is clear effect of accumulated experience and aging, see also Sturman (2003). Moreover, intuitively, the asymptotic output in the long run must be zero. Therefore, we suggest yet another widely accepted unimodal learning curve:

$$A_i(t) = \alpha_{1i}(e^{-\alpha_{2i}t} - e^{-\alpha_{3i}t}), \quad i \in V. \quad (2)$$

Both models are three-parametric and all parameters are non-negative reals. We refer to the first and to the second performance curves as the learning curves *without* and *with aging effect*, respectively.

Resource-sensitive performance

The second term of employee performance is the output generated by resource utilization. Clearly, this term must positively react on the amount of resources assigned to the employee. For a scarce countable resource, e.g., a number of PhD students assigned to a professor, it is reasonable to assume that the output increases linearly in the amount of the resource. For non-scarce (discrete or continuous) resource, e.g., workstations or money, marginal performance decreases in the amount of resource. In this case, we assume that the output function is logarithmic in the amount of the assigned resource.

Likewise in the personal performance, we introduce two types of learning curves, without and with aging, to account for the employee learning in the resource utilization process. Here, the models for resource sensitive performance without aging read as follows

$$B_i(p, t) = \beta_{1i} \left(\frac{1 - e^{-\beta_{2i}t}}{1 + e^{-\beta_{3i}t}} \right) p, \quad i \in V; \quad (3)$$

$$B_i(p, t) = \beta_{1i} \left(\frac{1 - e^{-\beta_{2i}t}}{1 + e^{-\beta_{3i}t}} \right) \ln(1 + \beta_{4i}p), \quad i \in V, \quad (4)$$

where p is the resource assigned to an employee, Eq. (3) models the scarce resource case with linear performance reaction and Eq. (4) models the non-scarce resource case with logarithmic performance reaction. Respectively, the models with aging effect and linear/logarithmic performance sensitivity read:

$$B_i(p, t) = \beta_{1i}(e^{-\beta_{2i}t} - e^{-\beta_{3i}t})p, \quad i \in V; \quad (5)$$

$$B_i(p, t) = \beta_{1i}(e^{-\beta_{2i}t} - e^{-\beta_{3i}t}) \ln(1 + \beta_{4i}p), \quad i \in V. \quad (6)$$

Notice, in the models above we deliberately do not specify the time moment when the resource is assigned to the employee. If an immediate effect of the resource assignment is expected, then $p = p_{it}$. If there is a response delay, i.e., the resource boosts the performance with a delay of $\tau > 0$, then $p = p_{i,t-\tau}$. We refer to this phenomena as the *resource response delay*. The delays might be assumed, expected, guessed or computed from historic data. We leave out further discussion on this matter. In our computational experiments for the PhD students allocation case, the resource response was delayed on average by about 2 years, meaning that a joint work of a professor with a student turns into publications on average in 2 years from the beginning of a project. These terms reveal the reality in the research field of the mimicked lab.

In some applications, the learning effect takes place only if an employee receives the resource, otherwise her learning curve remains at the same level or even degrades. Moreover, the learning effect might also depend on the amount of the resource assigned to the employee. We refer to this phenomena as *personal learning experience*. In our illustrative example, we rather assume the *common learning experience*, when the supervision and progress on research projects are observed by the entire lab and professors can and do learn from each other.

Communication-sensitive performance

In this section we discuss an additive term of employee performance responsible for information exchange. In case of imperfect information, namely, when the employees do not know the amount of resources assigned to others, the personal performance plus the resource-sensitive performance usually suffice. However, in many applications, including the academic lab example, the resource allocation is directly observed by all employees. Thus, we may assume a perfect information case, though imperfect information and mixed cases are not uncommon. Knowing the resource allocation, an employee performance usually changes. This could be driven by ambition to be the best, envy, anger and/or other spontaneous but long lasting reactions (Schaubroeck & Lam, 2004; Tai et al., 2012; Lee & Duffy, 2019). For instance, if two employees, knowing each other and having comparable performances, receive drastically different amount of the resource, the employee that gets less reacts on the resource allocation by either increasing performance, e.g., capitalizing on their *positive responses*, or decreasing performance, e.g., losing on their *negative responses* (Tai et al., 2012). There is, of course, large portion of ambiguity in the use of these specific terms but they are rather indicative and we present them only for the sake of providing the intuition.

Now, we model the communication network of an organization. To this end, we introduce a directed graph $G = (V, A)$, where a vertex $i \in V$ denotes an employee and a directed edge/arc $(i, j) \in A$ indicates existence of communication between employees i and j . In our implementations, we assume consistency of the marginal performance in resource sensitive and communication sensitive terms, i.e., if resource sensitive performance is linear or logarithmic in the amount of the resource, then the communication performance is linear or logarithmic, respectively. Then, the accumulative effect of communication can be modeled as follows

$$C_i(\bar{p}, t) = \sum_{j \in V: j \neq i} \gamma_{ij} p_{jt}, \quad i \in V; \tag{7}$$

$$C_i(\bar{p}, t) = \sum_{j \in V: j \neq i} \gamma_{ij} \ln(1 + \delta_{ij} p_{jt}), \quad i \in V, \tag{8}$$

where \bar{p} is the vector of resource allocation. Notice, in practice, graphs G are very sparse as the resource allocation influence on employees performance does not extend beyond a closed group of employees. For instance, resource allocation in one academic lab does not influence the performance of another academic lab. Typically, the degree of a vertex in the graph is up to six. Therefore, for each employee we have to determine through the regressions at most six parameters in Eq. (7) and at most twelve parameters in Eq. (8).

An interesting and practically relevant extension of the model is tackling the memory effect. Here, an employee reacts not only on the current resource allocation but remembers also the allocation of previous periods. This can amplify the effect of communications. In this case, the change in the equations above is quite straightforward. For instance, the linear model of communication sensitive performance can be rewritten as follows

$$C_i(\bar{p}, t) = \sum_{0 \leq \tau \leq t} \sum_{j \in V: j \neq i} \gamma_{ij} e^{-\zeta_{ij}(t-\tau)} p_{j\tau}, \quad i \in V. \quad (9)$$

Clearly, the more setting and effects we bring into the model the more degrees of freedom we consume. Thus, we have to be cautious regarding the necessity of model parameters. Details, tips and tricks for the feature selection we present in the computational study below.

Last but not least, we hypothesize on how the global resource allocation in the organization influences the individual performance of employees. The closest intuitive notions here are *pride*, when the individual performance of an employee positively reacts on the resource allocation to her organizational unit, and *snobbery*, when this effect is negative. Think of the following example: an employee working in a resource rich unit has an additional incentive and motivation compared to an employee from a resource poor unit. For simplicity and transparency, in our computational experiments we omit this ingredient of individual performance.

Forecasting employee performance

The general model of an employee performance in period t is given by

$$Y_i(\bar{p}, t) = A_i(t) + B_i(p_{it}, t) + C_i(\bar{p}, t), \quad i \in V. \quad (10)$$

Provided historic data, personal output and resource allocation over time, it is straightforward to obtain all parameters (coefficients α, β, γ) in the models (1)–(9) through the conventional regression analysis. This provides an organization with a simple and very intuitive tool for forecasting the future personal performance of the employees working sufficiently long in the organization. The only remaining question for the forecast is to construct a performance model for a *novice* when the historic data of her output in the specific environment of the organization does not exist or it does exist but very limited, i.e., the number of observations is insufficiently representative to proceed with the regression analysis. We model the performance of a novice using, though implicitly, fuzzy sets. In the nutshell, we see the current and the past employees as weighted prototypes for the novice. In the beginning, when there is no information about the novice, the weights of all prototypes are equal, subject to possible demographic corrections. Over time the novice is creating her own history of observations. Then, the prototypes which do not match the novice observed data receive less weights than the matching prototypes.

Now, we describe the model of a novice performance in detail. Assume the organization has at least one employee for prototyping, i.e., an employee with at least Q historic observations of the resource and output, where Q is large (representative) enough to make regression analysis meaningful. Thus, we assume that for each prototype i , the performance $Y_i(\bar{p}, t)$ is modeled by Eq. (10) and all parameters in all terms of Eq. (10) are known from the regression. Without loss of generality, let the number of “old” prototypes/employees be n , let a single novice be indexed by $i = 0$, and let $0 \leq t < Q$ time periods elapsed since the

novice’s first day of employment. Clearly, for any time period $0 \leq \tau \leq t$ we have observables: amount of the resource $p_{0\tau}$ assigned to the novice and her performance $Y_0(\tau)$. For $t < \tau \leq Q$, when historic data for the novice is unavailable, let

$$\tilde{Y}_0(\bar{p}, \tau) = \sum_{i=1}^n w_i Y_i(\bar{p}, \tau), \tag{11}$$

where the weight w_i of a prototype $i \in V \setminus \{0\}$ is to be determined later. Computing Eq. (11) we obtain the lacking values for the regression. Then, we perform the regression analysis and the resulting function $Y_0(\bar{p}, t)$ is the forecast for the novice. Notice that the regression-based forecast may differ from the forecast \tilde{Y}_0 modeled by the prototypes. Also notice that we do not use any novice for prototyping till a novice reaches the milestone of Q time periods in the organization.

Now, we address the issue how to assign weights to the prototypes. At the beginning of any novice career, i.e., $\tau = 0$, we assume all weights are equal $w_i = 1/n, i \in V \setminus \{0\}$. Of course, the initial weights might be assigned in a more sophisticated way, e.g., taking into account similarity of the novice to the prototype in the education and/or experience, age, gender etc. For simplicity reasons, we assume we have no information on these demographic factors. We also may assume that the performance of any novice consists of only two additive terms: $Y_0(p_{0t}, t) = A_0(t) + B_0(p_{0t}, t)$ for every $1 \leq t \leq Q$. This is because there is always a substantial delay in communication sensitivity: a novice must first learn the environment and the network and only then she becomes sensitive to the resource allocation. Think of a novice observing an experienced employee getting the resource. We assume the novice learns from the resource utilization of the experienced employee while remaining indifferent to the amount of the resource assigned to the colleague. In our model, the time moment when the novice becomes communication sensitive coincides with Q . This coincidence is assumed only for the sake of simplicity.

Let $0 \leq t < Q$ time periods elapsed since the first day of employment of the novice. We have observed her performance in t time periods, $Y_0(p_{01}, 1), Y_0(p_{02}, 2), \dots, Y_0(p_{0t}, t)$, where $p_{01}, p_{02}, \dots, p_{0t}$ are the respective amounts of the assigned resource. Moreover, we have performance forecasts $Y_i(p_{it}, t)$ for all prototypes $i \in V$ for all $t \in \mathcal{T}$. Consider a t -dimensional space \mathbb{R}^t . We “place” a novice in the point $(Y_0(p_{01}, 1), Y_0(p_{02}, 2), \dots, Y_0(p_{0t}, t)) \in \mathbb{R}^t$. Respectively, we “place” a prototype employee $i \in V$ in $(Y_i(p_{i1}, 1), Y_i(p_{i2}, 2), \dots, Y_i(p_{it}, t)) \in \mathbb{R}^t$. Here, we give each prototype exactly the amount of resources given to the novice. Clearly, the further the novice point from the point of a prototype, the less similar that prototype to the novice. Without loss of generality, assume all prototype points are distinct from the novice point, otherwise we put a weight of 1 to the prototype co-located with the novice and zero weight to all other prototypes. Let ρ_{i0} be the Euclidean distance from the point of novice to the prototype i point. For each $i \in V$, define

$$w_i = \frac{1/\rho_{i0}}{\sum_{i \in V} 1/\rho_{i0}}. \tag{12}$$

Since the prototype points are distinct from the novice point, all weights are well defined. This completes the forecast construction for a novice.

We have a couple of final remarks on the weight construction. First of all, the demographic data discussed above might be included as additional dimensions in the space where we “place” the employees. In this case, even the initial weights will be non-uniform.

Second, one might say that in the beginning of employment there is less certainty in classifying a novice, i.e., in proper weighting the prototypes. To this end, one may introduce a *dimension discount* factor $\delta > 0$ such that the contribution of time moment τ , $1 \leq \tau \leq t$, to the Euclidean distance comes with a factor of $e^{-\delta(t-\tau)}$:

$$\rho_{0i} = \sqrt{\sum_{1 \leq \tau \leq t} e^{-\delta(t-\tau)} (Y_0(p_\tau, \tau) - Y_i(p_\tau, \tau))^2}. \tag{13}$$

Computing the factor δ is an interesting issue in itself but we defer this study to the future work.

Optimal resource allocation

We utilize the constructed forecasts in the algorithms computing the resource allocation that maximizes the total output of the organization. To this end, many well-known criteria can be embedded into the framework, e.g., maximizing the total performance over the time horizon, maximizing the minimum performance over the time horizon, maximizing the minimum employee performance in the long run and many others. Further, we illustrate the algorithms on the most straightforward and intuitive criteria when the total performance of all employees over the time horizon is maximized. Consider the case where the resource is renewable and continuous. Moreover, let the resource and communication sensitive performances be linear in the resource with no aging and memory effects, i.e., the performances are determined by Eqs. (3) and (7), respectively. Then, the optimization model is also linear and after rearranging the terms it reads:

$$\begin{aligned} & \max_{p_{it} \geq 0} \sum_{i \in \mathcal{I}} \sum_{i \in V} \left(\beta_{1i} \left(\frac{1 - e^{-\beta_{2i}t}}{1 + e^{-\beta_{3i}t}} \right) + \sum_{j \neq i} \gamma_{ij} \right) p_{it} \\ & \sum_{i \in V} p_{it} \leq P(t), \quad \forall t \in \mathcal{T}, \\ & 0 \leq p_{it} \leq p_{\max}, \quad \forall i \in V; \forall t \in \mathcal{T}, \end{aligned}$$

which can be straightforwardly decomposed into a set of \mathcal{T} trivial continuous *knapsack* problems, one for every $t \in \mathcal{T}$, having the following optimal solutions. Denote $d_{it} = \beta_{1i} \left(\frac{1 - e^{-\beta_{2i}t}}{1 + e^{-\beta_{3i}t}} \right) + \sum_{j \neq i} \gamma_{ij}$, $i \in V$ and $t \in \mathcal{T}$. For every $t \in \mathcal{T}$, arrange d_{it} in a non-increasing order and in this specific order give the maximum possible resource to the employees unless the assigned resource hits the budget $P(t)$. Formally, the procedure is as follows. Without loss of generality, assume $d_{1t} \geq d_{2t} \geq \dots \geq d_{nt}$. Initialize the computation with $P_t := 0$, $k := 1$ and $p_{it} := 0$ for all $i \in V$. While $P_t + p_{\max} \leq P(t)$, let $p_{kt} := p_{\max}$, $P_t := P_t + p_{\max}$, and $k := k + 1$. If $k = n$ then stop. If $P_t + p_{\max} > P(t)$ then $p_{kt} := P(t) - P_t$ and stop. In other words, we provide the maximum resources to the employees with the maximum marginal resource sensitivity.

For logarithmic resource and communication sensitivity, one has to derive straightforward Karush–Kuhn–Tucker conditions. We leave this as a very simple exercise to the reader.

Since the knapsack problem above has trivial (unweighted) budget constraints, the cases with renewable discrete resources can be tackled similarly to the continuous ones. For the

case of non-renewable resources, e.g., monetary budget for the entire time horizon, the budget constraint becomes $\sum_{i \in \mathcal{I}} \sum_{i \in \mathcal{V}} p_{it} \leq P$, where P is the total budget for the time horizon. In this case, coefficients d_{it} must be arranged not per time period but globally. All other calculations and derivations remain intact.

It comes naturally that the optimal resource allocation assigns the resources to the employees with the highest response to the resource assignment. Unfortunately, if the resources are distributed this way, selfishly behaving employees might start playing strategically to maximize their own utilities, e.g., resource share. The following strategy will suffice their selfish objective. If in a certain time period the resources are assigned to the employee, she produces as much output as possible. During the periods when no resources or little resources are assigned to her, the employee under-performs, say, she does not produce any output. Then, the performance predictive regression produces the steepest possible slope indicating the highest possible response to the resource assignment. Therefore, the employee receives the maximum possible resources while the organization does not receive the maximum total output. Thus, the above linear/mathematical program can serve only as an upper bound for the total employer's output. This upper bound is hardly attainable in practice but may be used as the output benchmark/target. We refer to this benchmark as the *optimal resource allocation*.

Performance-driven and uniform resource allocations

In practice, organizations implement simple, transparent and seemingly fair resource allocation schemes. To this end, our optimal resource allocation can be seen as the main practical deliverable of the paper as from now on an organization may compare their resource allocation schemes to the benchmark and compute the absolute or relative *price of simplicity/transparency/fairness*. To illustrate this price of simplicity/transparency/fairness, in our computational experiments in the sections below, we compare two most frequently implemented in practice resource allocation schemes to the proposed benchmark.

The first resource allocation scheme assigns the resources according to the output generated by the employees. This resembles a widely accepted *greedy* allocation rule: the higher the forecasted performance of an employee, the more resources she gets. In our example with professors, we use this rule to its extreme. Namely, we look at the performance forecast of every individual professor assuming she receives p_{\max} students. We select the best performer, give her exactly p_{\max} students and exclude her from the following steps of allocation procedure. Then, we decrease the available resource capacity $P(t) := P(t) - p_{\max}$ and recur until $P(t) < p_{\max}$. In the very last step, we give the remaining capacity $P(t)$ to the best performing professor with $P(t)$ students and we stop as the other professors receive no PhD students. We refer to this scheme as *performance-driven resource allocation*. The performance-driven resource allocation certainly anticipates any under-performance, no matter strategic or not. On the other hand, this allocation strategy can easily be sub-optimal as a very productive employee might be extremely non-responsive to the resource assignment. Then, the resources given to such employee are simply wasted and the organization does not reach the desired output. In our illustrative example, a professor might be very productive on her own, but assigning many students to this professor might even be counterproductive.

The second widely implemented scheme simply assigns the resources uniformly among all employees at any moment in time. We refer to this second scheme as the *uniform*

resource allocation. The benefit of this seemingly fair scheme is that some negative effects of communication sensitive performance are also anticipated. On the other hand, the positive effects of personal and communication-sensitive performance are also diminished, which is clearly the downside of the uniform allocation scheme.

An illustrative example, continued

A simulation model was created based on historical data of the existing scientific laboratory (specializing in Operations Research) of one of the West-European universities, see Table 4 in the appendix. One can see this simulation as random perturbation of starting dates of professors' employed in the real lab. A data set obtained from the simulation becomes the input for our computational experiment. In Table 4, the column *Year*—the years from 1999 to 2018, which is the historic time span; *S*—the number of years of employment of a professor in the laboratory; *Y*—the performance value (number of papers published) over the years; *p*—the number of PhD students allocated to a professor over the years. Notice, in several occasions the number of PhD students assigned to one professor exceeds three. This doesn't contradict to the claim that at most three students are assigned to a professor because the three students restriction is a condition on a desired solution and not on the real data.

There are eight professors in the lab, see Table 4. One of the professors, $i = 8$, in the data set is a novice working in the lab only three years so far. Without loss of generality, assuming $Q = 9$, we use the seven "old" professors as prototypes to forecast the novice performance. Using standard regression tools in MATLAB R2015a (c), we first compute parameters of model (10) for each professor $i = 1 \dots 7$. Then, we model the performance of the novice as described in Sect. 4. Then, given the performance forecasts for all professors, we examine several typical resource allocation schemes, including the optimal benchmark case. If we want to maximize the performance over several years, for every upcoming year we introduce the forecasted values as observables and recourse on the updated data set.

We have to make a disclaimer that the sample data we are dealing with is very small. This toy application and the data-set are provided purely for illustrative purposes though resemble the real-life situation in an operations research group of a European university. Surprisingly, even on this small example we observe a nice performance of this toolkit. If one would have a data-set with more frequent observations, e.g. daily performance of IT specialists or programmers within a couple of IT or software development projects, the outcome of the suggested methodology would provide a performance benchmark of all employees and a solid ground for further resource allocation.

Performance forecasts

For intuition and transparency, we slightly simplify model (10) letting

$$Y_i(t, p) = \alpha_i + B_i(p, t) = \alpha_i + \beta_{1i} \left(\frac{1}{1 + e^{-\beta_{2i}t}} \right) p, \quad i = 1 \dots 8. \quad (14)$$

Then, after applying the procedure described in Sect. 4, the regression results for eight professors are presented in Table 1.

Table 1 Regression output, * p -value < 0.1; ** p -value < 0.05; *** p -value < 0.01

i	α_i	β_{1i}	β_{2i}	Model Sig-nificance	R^2
1	1.2225 ***	0.4693***	267.49***	0.001	0.389
2	1.3319 **	0.3749*	336.02***	0.111	0.116
3	0.9694**	0.5145***	77.85***	0.001	0.478
4	1.7946***	1.2251	-0.48	0.373	0.116
5	0.9083*	0.8703***	1.24	0.003	0.676
6	1.4837***	0.2829	0.13	0.546	0.058
7	1.5601***	0.6270	0.08	0.038	0.290
8	0.5634	1.1483**	1.74***	0.007	0.564

The first three columns introduce individual significance of coefficients α , β_1 and β_2 , while the overall significance and explanatory power of the model are reported in the last two columns, respectively. Particularly, in this table we read that the constructed model is significant and well explaining performances of five professors out of eight: model generally works for professors 1, 3, 5, 7 and 8, while the results for the other professors, 2, 4, and 6, do not look promising. Notice, aiming for a model perfectly explaining academic performance in any case for any individual sounds not realistic and hardly possible. In our opinion, getting workable models for performance prediction in five out of eight cases is already a good achievement.

Resource allocations

In our case, every year we have to allocate ten PhD students among eight professors. In addition we have a constraint that at most three PhD students can be simultaneously allocated to a professor. In this section, we report on three different allocation principles, described in Sects. 5 and 6.

- Optimal (benchmark) resource allocation, where the professors with the highest response to the PhD allocation receive the highest volume of the resource. Here, the response is computed by $\beta_{1i} \left(\frac{1}{1+e^{-\beta_{2i}t}} \right)$, $i = 1 \dots 8$, see Sect. 5. In the case at hands, 3 out of 8 professors with the highest responses will get 3 PhD students each, 1 professor with the forth highest response will receive one student, and the other 4 members of the lab will get no students.
- Performance-driven allocations: the higher the forecast output of a professor is, the more PhDs will be given to her. In our case again, 3 out of 8 professors will get 3 students each, 1 professor will be given one student, and the other 4 professors will get none.
- Uniform allocation (each professor gets 10/8 of PhD students meaning that one should share the students allocated with the other professors);

In order to compare the allocation schemes, we are going to predict performance of each of the eight professors knowing the regression coefficients α_i , β_{1i} , β_{2i} , $i = 1, \dots, 7$, and depending on the number of PhDs allocated to every professor. Table 2 summarizes the forecast results for the year 2019.

Table 2 Professor’s performance prediction for the year 2019

<i>i</i>	<i>t</i>	0 PhDs	1 PhD	2 PhDs	3 PhDs
1	19	1.2225	1.6918	2.1611	2.6304
2	20	1.3319	1.7068	2.0817	2.4567
3	16	0.9694	1.4839	1.9984	2.5129
4	16	1.7946	1.7951	1.7957	1.7962
5	10	0.9083	1.7786	2.6488	3.5191
6	20	1.4837	1.7479	2.0121	2.2763
7	19	1.5601	2.0797	2.5993	3.1189
8	4	0.5634	1.7106	2.8578	4.0050

Table 3 Lab 2019 predicted performance under different resource allocations

Resource allocation	Performance, # papers	Performance loss, %
Optimal	17.9596	–
Performance-driven	17.4456	2.86
Uniform	15.0346	16.29

Table 4 Employee simulated data

Year	<i>S</i> ₁	<i>Y</i> ₁	<i>p</i> ₁	<i>S</i> ₂	<i>Y</i> ₂	<i>p</i> ₂	<i>S</i> ₃	<i>Y</i> ₃	<i>p</i> ₃	<i>S</i> ₄	<i>Y</i> ₄	<i>p</i> ₄	<i>S</i> ₅	<i>Y</i> ₅	<i>p</i> ₅	<i>S</i> ₆	<i>Y</i> ₆	<i>p</i> ₆	<i>S</i> ₇	<i>Y</i> ₇	<i>p</i> ₇	<i>S</i> ₈	<i>Y</i> ₈	<i>p</i> ₈
1999	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2000	0	0	0	1	2	3	0	0	0	0	0	0	0	0	0	1	2	3	0	0	0	0	0	0
2001	1	0	1	2	1	1	0	0	0	0	0	0	0	0	0	2	0	8	1	4	2	0	0	0
2002	2	2	1	3	3	2	0	0	0	0	0	0	0	0	0	3	2	3	2	2	1	0	0	0
2003	3	3	2	4	3	2	0	0	0	0	0	0	0	0	0	4	1	1	3	2	2	0	0	0
2004	4	1	0	5	2	2	1	0	3	1	3	3	0	0	0	5	0	1	4	2	0	0	0	0
2005	5	1	0	6	0	3	2	1	2	2	1	2	0	0	0	6	3	2	5	2	2	0	0	0
2006	6	1	2	7	2	3	3	5	4	3	3	3	0	0	0	7	2	3	6	1	1	0	0	0
2007	7	2	1	8	5	3	4	2	4	4	1	2	0	0	0	8	1	2	7	2	2	0	0	0
2008	8	2	3	9	1	2	5	2	5	5	3	2	0	0	0	9	1	1	8	2	1	0	0	0
2009	9	1	0	10	3	2	6	3	1	6	2	1	0	0	0	10	1	2	9	4	1	0	0	0
2010	10	3	4	11	2	3	7	4	2	7	2	2	1	0	3	11	2	2	10	3	1	0	0	0
2011	11	1	1	12	2	2	8	2	3	8	2	1	2	1	3	12	4	3	11	2	3	0	0	0
2012	12	3	3	13	3	4	9	1	1	9	1	3	3	3	2	13	1	3	2	1	3	0	0	0
2013	13	1	4	14	1	2	10	3	2	10	2	3	4	4	2	14	4	2	13	1	0	0	0	0
2014	14	3	1	15	3	1	11	3	1	11	2	2	5	3	2	15	3	1	14	1	2	0	0	0
2015	15	3	2	16	1	2	12	2	2	12	2	2	6	2	3	16	1	0	15	3	2	0	0	0
2016	16	2	3	17	2	2	13	2	2	13	0	2	7	4	0	17	2	0	16	3	5	1	0	3
2017	17	3	3	18	3	2	14	1	3	14	2	1	8	5	4	18	1	2	17	1	2	2	3	2
2018	18	3	1	19	2	4	15	3	3	15	1	1	9	1	3	19	2	4	18	5	4	3	5	1

Here, t stand for the number of employment years of a professor in 2019. Then, one should read the table as follows. If no PhD students are assigned to professor 1 in 2019, her output in that year is estimated at level of 1.2225 papers. Similarly, for every professor and for every number of PhD students, we report on the specific performance forecast. All these figures are the results of straightforward calculation of $Y_i(t, p)$ using Eq. (14) with coefficient from Table 1.

Using Table 2, we can compare three types of resource allocations discussed in Sects. 5 and 6. Assume one wants to maximize the total output of the lab in 2019. The forecasts for the total lab output in 2019 under different allocation scenarios are reported in Table 3.

For instance, when computing the predicted lab performance in the optimal benchmark as described in Sect. 5, we end up with the following solution. Professor 8 has the highest response to the assigned resources and she is followed by professors 5, 7, and 3 in this particular order. The response values are not reported in the tables—we leave it to the reader to verify the order by directly computing the response values with the formula above. Therefore, professors 8, 5, and 7 receive 3 PhD students each, professor 3 receives only one student, and professors 1, 2, 4 and 6 receive 0 students. Picking up the corresponding forecasts in Table 2, we derive the optimal output of the lab of 17.9596 publications. From Table 1 it is visible with naked eyes that professor 8 is highly responsive to the resource provision with a jump from 0.5634 publications with no PhDs to 4.0050 publications with three PhDs. The least responsive professor is professor 4: she publishes about 1.8 papers a year regardless the number of students. Interestingly, looking at the raw data in Table 4, we were not able to recognize this phenomena of both professors, 8 and 4. For professor 8 it is easily explainable as she is novice, there is no data associated with her, and she receives a special treatment with the fuzzy sets by picking responsive professors as prototypes. The fact that professor 8 becomes the most resource sensitive we cannot explain. In turn, professor 4 is an old professor, working in the lab for 15 years. Her performance is predicted based on the learning curve (regression) model. It seems, for the learning curve, her observable results were too steady and independent on the number of students: the α_4 coefficient is highly significant while both, β_1 and β_2 , are not. These few observations for specific professors provide a good intuition on how to look at the numbers in the tables.

In the performance-driven allocation, professors 8, 5, and 7 are leading again; see the column “3 PhDs” in Table 2. When 9 PhD students are allocated to these professors and only one PhD student remains for allocation, we have to look in column “1 PhD” for the next best professor. This is professor 4, not 3. Thus, this professor receives one PhD student. As we have just discussed, professor 4 performs on a level of 1.8 papers a year regardless the number of students. Thus, it is suboptimal to give her resources when there are professors with a higher response value, e.g., professor 3. This is why performance-driven allocation heuristic fails to find an optimal solution in this case. Nevertheless, under performance-driven allocation, the forecast for the total number of lab publications 17.4456 is still good being only 2.86% below the optimum. If resources are distributed uniformly among all professors, i.e., $p = 10/8$, the total number of publications drops to 15.0346, which is 16.29% off the optimum, being the poorest performer among the three allocation schemes.

Discussion

In this section, we discuss how well did we solve the problem of constructing a simple, computable, dynamic, and intuitive model for employee performance measurement, management and optimal resource allocation. These features were announced in Sect. 3 as required distinctive properties of the model. If the construction is successful, it will be the first model combining all these features at once. We also list other advantages and limitations of the constructed model, and we put our findings in the context of the existing literature on performance measurement and management.

Model simplicity and computability

All our measurements are straightforward and intuitive. We take as input only simple and essential observables: produced output and utilized resources. There are no speculations on complex issues—we defer these to post-computing analysis not even trying to establish any correlation and/or causality. Therefore, our performance measurements are much simpler than the models known in the contemporary literature (Motowidlo et al., 1997; Hogan & Shelton, 1998; Baard et al., 2014; Carpini et al., 2017). Notice, we regard simplicity as an advantage here since our aim is to establish a very practical, operational and manageable tool for decision makers working with personnel.

Moreover, to overcome the issues of talent performance complexity and personal data processing, we do not dive into the structure of the very essence of talent performance and deliberately do not use complex tools associated with difficulties to interpret the results numerically (Goodman & Flaxman, 2017). We accept that we will not be able to take into account all the aspects and parameters of talent performance. At the same time, our model gives us a chance to introduce a convincing “black box” tool calculating the employee performance on the basis of conventional regression analysis with nicely interpretable results.

Dynamic performance

Compared to the articles in Sect. 2, we want to trace the performance over time. It is, of course, our assumption that the performance undergoes a life cycle in accordance with some learning curves. On the other hand, such an assumption allows us to understand and explain academic performance in a natural way, which also contributes to better communication of the results to the academic managers and planners.

We consider learning curves in application to talents' performance (Simonton, 1997; Howard, 2009, 2014, 2018; Weinberg & Galenson, 2019) as a feasible approach to modelling despite the complex nature of the knowledge workers' performance (Boh et al., 2007). Of course, employees cannot consistently apply their cognitive abilities, skills and experience over time (Weiss & Merlo, 2020), so we can easily observe changes and irregularities in the employee performance. Nevertheless, the “eigen” performance component in our model can be seen as a smoothed version of the real individual performance curve.

Capturing in the model the most intuitive and natural factors

In our approach we deviate from the common practice of performance determination through the task, adaptive and contextual performances (Motowidlo et al., 1997; Baard et al., 2014; Carpini et al., 2017). From operational point of view, this complicates the measurement drastically and it becomes a hard job to convince managers that the model is doing what it supposed to do. In contrast to the complicated approach, we assume only three extremely naive and very natural things: the performance of an academician depends on her position on a learning curve, on the quantity of the resources she receives and on the quantity of resources other colleagues and/or competitors receive.

Focusing on resources is the key in our approach. We use resources as means of managerial interventions influencing employee performance. Notice, in real life, the number of tools available for managers to strive the performance is limited. In our example of an academic lab, resource allocation, team composition, information provision, tenuring and promotions, non-research tasks and training distribution are usually regarded as available managerial instruments. Taking into account the university specifics, distribution of the PhDs in an academic research group plays a significant role in research development and publications (van den Brink et al., 2013). We also regard the interventions as those independent variables that lead to changes in the organization performance over time, nicely coming back to the dynamic nature of our model.

Limitations

As for any model of any sophisticated phenomenon, our approach has also several limitations. We admit that the very fact of the resource allocation will affect not only the direct outcome in the form of publications, but also the perception of such allocations, which in turn will affect individual performance. It gives grounds for including the components of the talents' perception of the fairness of the resource allocation (Smither, 2012) and their subsequent influence on the behavioral changes of the talent. In our model, we suggest a resource allocation which guarantees the optimal output only under very strong economic assumptions of cooperative behavior of all employees. In reality, however, researchers might have their individual utilities not coinciding with the organizational goals and thus, they might start behaving strategically (Maux et al., 2015). In this paper, we make the first move towards exploring mechanisms mitigating such strategic behavior. We suggest considering two simple and widely used resource allocation schemes, performance-driven and uniform resource allocations. However, attacking this issue in a systematic way requires very serious analysis which goes far beyond the targets of the present paper.

To pursue simplicity and applicability of the model, we deliberately simplify organizational goals of an academic unit to be just the number of (possibly weighted) publications. Due to its high level of objectivity, this is definitely one of the main performance measures in the academic environment (van den Brink et al., 2013). However, this is not the only one and in the academic communities across the globe, there is a big debate on much more comprehensive measures of academic performance.

We should also notice that the use of nonlinear regressions raises the issue of choosing the right setup parameters in the software packages computing the model coefficients. Typically, the output in standard packages for non-linear optimization is quite sensitive to setup parameters, e.g., precision, choice of routines, initial values, number

of branches and so on. The reason for such sensitivity is that the resulting solution is a local, and not the global, optimum in the underlying optimization problem. Unfortunately, this limitation is quite difficult to overcome when using standard industrial software packages.

Conclusion and future research directions

Summarizing the above discussion and the model properties, we conclude that the constructed model offers all promised features: simplicity, tractability, dynamic and intuitive nature. This is the first model of such kind dealing with the combination of employee performance management and resource allocation. The benefits of the model are twofold. For the academic community, the model provides a systematic and, most importantly, intuitive view on individual and organizational performance development and its dynamics. The results can be seen as benchmarks and they should be exercised against other, more sophisticated, performance measures and managerial practices. For managers, the model offers a direct, very prescriptive and pragmatic approach to recognize talents and to manage their performance via resource allocation. Because of simplicity, intuitive nature, and usage of only standard machineries, the methodology becomes very convincing for and easily implementable in real organizational environment.

A few important questions remain open. First, how often do we need to measure performance and adjust the developed model? To answer this question, it would be reasonable to refer to the planning horizon, the expected time period for obtaining the results, as well as the degree of digitalization within the organization (Angrave et al., 2016; Levenson & Fink, 2017). The simplified example of professors, whose performance is measured in papers published per year, implies an annual monitoring of the results with a planning horizon of roughly 10–20 years. However, if the organization can record daily progress of employees (for example, within IT projects), then the model allows for daily monitoring. Further extensions and inclusion of variables are possible and flexibly accepted by the model, but require further analysis.

One more important part of modelling decision support systems is sensitivity of data used in terms of ethics and legal rights of employees. In our model we deliberately omit age, gender and other demographic variables and concentrate our attention mostly on such input as produced output and utilized resources. To understand the influence of those variables which can be related to any bias in the organisation, they should be included explicitly in the model.

For the sake of visualization, in our illustrative example, we simplified the model, e.g., by omitting the communication-sensitive performance component. The use of the full range of components in the model will give us an opportunity to better evaluate talents' potential, predict performance at individual, team, and organizational levels, recognize contextual performance and talents' response to changes, build networks of leadership and evaluate communications. Of course, this requires a bigger and richer data set than the presented one. Hence, testing the model on a large data set with a larger set of model coefficients will be not only more convincing but also very insightful.

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References

- Alessandri, G., Borgogni, L., & Truxillo, D. M. (2015). Tracking job performance trajectories over time: A 6-year longitudinal study. *European Journal of Work and Organizational Psychology, 24*(4), 560–577.
- Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal, 26*(1), 1–11.
- Anzanello, M. J., & Fogliatto, F. S. (2011). Learning curve models and applications: Literature review and research directions. *International Journal of Industrial Ergonomics, 41*, 573–583.
- Argote, L. (1996). Organizational learning curves: Persistence, transfer and turnover. *International Journal of Technology Management, 11*(7/8), 759–769.
- Baard, S. K., Rench, T. A., & Kozlowski, S. W. J. (2014). Performance adaptation: A theoretical integration and review. *Journal of Management, 40*(1), 48–99.
- Bjorkman, I., Ehrnrooth, M., Makela, K., Smale, A., & Sumelius, J. (2013). Talent or not? Employee reaction to talent identification. *Human Resource Management, 52*(2), 195–214.
- Boh, W. F., Slaughter, S. A., & Espinosa, J. A. (2007). Learning from experience in software development: A multilevel analysis. *Management Science, 53*(8), 1315–1331.
- Campbell, G. M. (1999). Cross-utilization of workers whose capabilities differ. *Management Science, 45*(5), 722–732.
- Cappelli, P., & Keller, J. R. (2014). Talent management: Conceptual approaches and practical challenges. *Annual Review of Organizational Psychology and Organizational Behavior, 1*, 305–331.
- Carpini, J. A., Parker, S. K., & Griffin, M. A. (2017). A look back and a leap forward: A review and synthesis of the individual work performance literature. *Academy of Management Annals, 11*(2), 825–885.
- Collings, D. G., Mellahi, K., & Cascio, W. F. (2019). Global talent management and performance in multinational enterprises: A multilevel perspective. *Journal of Management, 45*(2), 540–566.
- Heidary Dahooie, J., & Ghezeli Arsalan, M. R. (2013). Applying fuzzy integral for evaluating intensity of knowledge work in jobs. *International Journal of Industrial Engineering Computations, 4*, 517–534.
- de Oliveira, E. C. B., Alencar, L. H., & Costa, A. P. C. S. (2018). Decision process of allocating projects to project managers. *Production Planning and Control, 29*(8), 645–654.
- Gallardo-Gallardo, E., Thunnissen, M., & Scullion, H. (2020). Talent management: Context matters. *The International Journal of Human Resource Management, 31*(4), 457–473.
- Glock, C. H., & Jaber, M. Y. (2014). A group learning curve model with and without worker turnover. *Journal of Modelling in Management, 9*(2), 179–199.
- Goodman, B., & Flaxman, S. (2017). European union regulations on algorithmic decision-making and a “right to explanation”. *AI Magazine, 38*(3), 50–57.
- Hogan, R., & Shelton, D. (1998). A socioanalytic perspective on job performance. *Journal of Management, 11*(2/3), 129–144.
- Howard, R. W. (2009). Individual differences in expertise development over decades in a complex intellectual domain. *Memory and Cognition, 37*(2), 194–209.
- Howard, R. W. (2014). Learning curves in highly skilled chess players: A test of the generality of the power law of practice. *Acta Psychologica, 151*, 16–23.
- Howard, R. W. (2018). Development of chess skill from domain entry to near asymptote. *American Journal of Psychology, 131*(3), 323–345.
- Jooss, S., McDonnell, A., & Burbach, R. (2019). Talent designation in practice: An equation of high potential, performance and mobility. *The International Journal of Human Resource Management*. <https://doi.org/10.1080/09585192.2019.1686651>.
- Kim, Y., Krishnan, R., & Argote, L. (2012). The learning curve of it knowledge workers in a computing call center. *Information Systems Research, 23*(3, Part 2 of 2), 887–902.

- Lai, Y.-L., & Ishizaka, A. (2020). The application of multi-criteria decision analysis methods into talent identification process: A social psychological perspective. *Journal of Business Research*, *109*, 637–647.
- Lee, K., & Duffy, M. K. (2019). Functional model of workplace envy and job performance: when do employees capitalise on envy by learning from envied targets? *Academy of Management Journal*, *62*(4), 1085–1110.
- Levenson, A., & Fink, A. (2017). Human capital analytics: Too much data and analysis, not enough models and business insights. *Journal of Organizational Effectiveness: People and Performance*, *4*(2), 145–156.
- Maux, B. L., Necker, S., & Rocaboy, Y. (2015). Cheat or perish? A theory of scientific customs. *Research Policy*. <https://doi.org/10.1016/j.respol.2019.05.001>.
- Dries, N., Meyers, M. C., & van Woerkom, M. (2011). Talent–innate or acquired? Theoretical considerations and their implications for talent management. *Human Resource Management Review*, *23*, 305–321.
- Minbashian, A., & Luppino, D. (2014). Short-term and long-term within-person variability in performance: An integrative model. *Journal of Applied Psychology*, *99*, 898–914.
- Motowidlo, S. J., Borman, W. C., & Schmit, M. J. (1997). A theory of individual differences in task and contextual performance. *Human Performance*, *10*(2), 71–83.
- Niessen, C., & Jimmieson, N. L. (2016). Threat of resource loss: The role of self-regulation in adaptive task performance. *Journal of Applied Psychology*, *101*(3), 450–462.
- Nijs, S., Gallardo-Gallardo, E., Dries, N., & Sels, L. (2014). A multidisciplinary review into the definition, operationalization, and measurement of talent. *Journal of World Business*, *49*, 180–191.
- Schaubroeck, J., & Lam, S. S. K. (2004). Comparing lots before and after: Promotion rejecteesHERE invidious reactions to promotees. *Organizational Behavior and Human Decision Processes*, *94*, 33–47.
- Shafer, S. M., Nembhard, D. A., & Uzumeri, M. V. (2001). The effects of worker learning, forgetting, and heterogeneity on assembly line productivity. *Management Science*, *47*(12), 1639–1653.
- Simonton, D. K. (1997). Creative productivity: A predictive and explanatory model of career trajectories and landmarks. *Psychological Review*, *104*(1), 66–89.
- Simonton, D. K. (2008). Scientific talent, training, and performance: Intellect, personality, and genetic endowment. *Review of General Psychology*, *12*(1), 28–46.
- Smither, J. W. (2012). Performance management. In S. W. J. Kozlowski (Ed.), *The Oxford handbook of organizational psychology*, chapter 10. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199928309.013.0010>.
- Sonnentag, S., & Frese, M. (2012). Dynamic performance. In S. W. J. Kozlowski (Ed.), *The Oxford handbook of organizational psychology*, chapter 17. Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199928309.013.0017>.
- Sturman, M. C. (2003). Searching for the inverted u-shaped relationship between time and performance: Meta-analyses of the experience/performance, tenure/performance, and age/performance relationships. *Journal of Management*, *29*(5), 609–640.
- Sturman, M. C. (2007). The past, present, and future of dynamic performance research. *Research in Personnel and Human Resources Management*, *26*, 49–110.
- Swales, S., & Blackburn, M. (2016). Employee reactions to talent pool membership. *Employee Relations*, *38*(1), 112–128.
- Tai, K., Narayanan, J., & McAllister, D. J. (2012). Envy as pain: Rethinking the nature of envy and its implications for employees and organizations. *Academy of Management Review*, *37*(4), 107–129.
- Tansley, C. (2011). What do we mean by the term “talent” in talent management? *Industrial and Commercial Training*, *43*(5), 266–274.
- Tansley, C., Kirk, S., & Tietze, S. (2013). The currency of talent management—A reply to “talent management and the relevance of context: Towards a pluralistic approach”. *Human Resource Management Review*, *23*, 337–340.
- Thunnissen, M. (2016). Talent management: For what, how and how well? An empirical exploration of talent management in practice. *Employee Relations*, *38*(1), 57–72.
- Thunnissen, M., & Van Arensbergen, P. (2015). A multi-dimensional approach to talent. *Personnel Review*, *44*(2), 182–199.
- Tyskbo, D. (2021). Competing institutional logics in talent management: Talent identification at the HG and a subsidiary. *The International Journal of Human Resource Management*, *32*(10), 2150–2184.
- Vaiman, V., Collings, D. G., & Scullion, H. (2017). Contextualising talent management. *Journal of Organizational Effectiveness: People and Performance*, *4*(4), 294–297.
- van den Brink, M., Fruytier, B., & Thunnissen, M. (2013). Talent management in academia: Performance systems and HRM policies. *Human Resource Management Journal*, *23*(2), 180–195.

- Weinberg, B. A., & Galenson, D. W. (2019). Creative careers: The lifecycle of Nobel laureates in economics. *De Economist*, *167*, 221–239.
- Weiss, H. M., & Merlo, K. L. (2020). Affect, attention, and episodic performance. *Current Directions in Psychological Science*, *29*(5), 453–459.
- Wiblen, S., & McDonnell, A. (2020). Connecting ‘talent’ meanings and multi-level context: A discursive approach. *The International Journal of Human Resource Management*, *31*(4), 474–510.
- Wu, Y.-J., & Hou, J.-L. (2010). An employee performance estimation model for the logistics industry. *Decision Support Systems*, *48*, 568–581.