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Can artificial neural networks predict lawyers' performance rankings?

Susana Almeida Lopes and Maria Eduarda Duarte
Faculty of Psychology, University of Lisbon, Lisbon, Portugal, and
João Almeida Lopes
Department of Pharmaceutics and Pharmaceutical Technology, Faculty of Pharmacy, University of Lisbon, Lisbon, Portugal

Abstract

Purpose – The purpose of this paper is to propose a predictive model that could replace lawyers' annual performance rankings and inform talent management (TM) in law firms.
Design/methodology/approach – Eight years of performance rankings of a sample of 140 lawyers from one law firm are used. Artificial neural networks (ANNs) are used to model and simulate performance rankings over time. Multivariate regression analysis is used to compare with the non-linear networks.
Findings – With a lag of one year, performance ranking changes are predicted by the networks with an accuracy of 71 percent, over performing regression analysis by 15 percent. With a lag of two years, accuracy is reduced by 4 percent.
Research limitations/implications – This study contributes to the literature of TM in law firms and to predictive research. Generalizability would require replication with broader samples.
Practical implications – Neural networks enable extended intervals for performance rankings. Reducing the time and effort spent benefits partners and lawyers alike, who can instead devote time to in-depth feedback. Strategic planning, early identification of the most talented and avenues for tailored careers become open.
Originality/value – This study pioneers the use of ANNs in law firm TM. The method surpasses traditional static study of performance through its use of non-linear simulation and prediction modeling.

Keywords Knowledge workers, Talent management, Performance appraisal, Neural networks, Career, Law firm

Paper type Research paper

1. Introduction

The new millennium brought to law firms an unusual drop in demand, lower rates and weaker client loyalty (Muir *et al.*, 2004; Stumpf, 2007). Law firms, which largely employ knowledge workers (Drucker, 1959), have identified talent as a differentiator during recessions (Cappelli, 2000; Gallardo-Gallardo *et al.*, 2013; Ready *et al.*, 2010). Talent management (TM) is used to attract, retain and develop the most talented lawyers, who are believed to add value to a firm's performance, creating competitive advantage and by depleting the reserves of competitors (Felin and Hesterly, 2007; Gallardo-Gallardo *et al.*, 2013).

In law firms, talent is equated with high performance (Brittain, 2005). The most talented lawyers are those who rank at the top of their firms in terms of performance. Thus, lawyers who exceptionally outperform their peers are frequently called the best in their class, the A Players, and the most talented (e.g. Ready *et al.*, 2010; Silzer and Dowell, 2010; Smart, 2005; Ulrich and Smallwood, 2012).

Such an approach to talent, which seeks to identify high performers for career advancement, fits the career model for law firms. In a tournament system that has its origins in the mid-nineteenth century in the USA, from admission into a firm to attaining partnership, each lawyer's performance is ranked annually against peers (Pinnington, 2011). High-performing lawyers are entitled to career advancement, and average and low-performing lawyers remain at the same professional level or are advised to leave the firm.

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Recent evidence supports the use of performance rankings to build a high-performing workforce, encouraging low performers to improve or to leave and releasing employees' best self to support the organization's success (Höglund, 2012; Netessine and Yakubovich, 2012). Notwithstanding, the annual ranking of the performance of a firm's lawyers is a highly bureaucratic endeavor that both partners and lawyers must undergo. Reliable prediction of the most talented would be of great value for practitioners, but this possibility remains a mirage. Prediction of performance rankings could allow more time to elapse between performance rankings. The time freed from this greatly disliked practice (Aguinis *et al.*, 2012) could be transferred to talent development and supporting career advancement.

This paper aims to fill this gap by proposing a way to predict performance rankings. Either statistical or intelligent methods can be used for prediction. In this paper, we propose the use of artificial neural networks (ANNs), an intelligent method of prediction that can, under certain conditions, outperform statistical methods.

The paper is organized as follows. First, it overviews TM in law firms, performance appraisal and competency frameworks. Second, it examines the potential use of ANNs to address performance rankings. Third, an ANN is proposed that was trained on eight years of lawyers' performance rankings to forecast performance rankings. For comparison purposes, a multivariate regression analysis is performed using the same data. Finally, the potential use of ANNs for TM in law firms is discussed.

2. Background

The economic slowdown in the first decade of the new millennium exposed firms to the experience of a drop in demand, followed by decreases in revenues and profits (Muir *et al.*, 2004). Even many highly prestigious firms have laid off workers in the USA, UK and other European countries. Several firms merged, whereas others closed entirely. The annual double-figure increases in revenue and profits resulting from annual fee increases are no longer. Clients, who are also facing tumultuous times, are managing smaller budgets and are pressuring providers, including law firms, for innovative service at lower fees.

The career model of the law firm was built around a hierarchical pyramid of partners, associates and trainees. It implied a continuous annual growth in profits, as well as in numbers of lawyers, for continuing career advancement and the creation of new partners each year (Galanter and Palay, 1990, 1994). Although the number of lawyers reaching partnership had always been few, the highest-performing lawyers could nevertheless expect this ultimate happy ending. This assumption of a reliable career path is now being defied. Although high-performing lawyers may not have a strong enough business case for making partner, their firms may also not be able to afford the loss of their talent (Mottershead, 2010).

Such challenges require a solution from law firms. The acknowledgment of the disproportionate contribution of the most talented to a firm's performance (Felin and Hesterly, 2007; Gallardo-Gallardo *et al.*, 2013) has embedded TM in the legal profession. Managing up-and-coming talent has been found to be vital in the support of firms' adaptation to the new normal (Davis, 2009), and talent is listed among the most critical assets in the sustainability of a firm (Boudreau and Ramstad, 2005). Large and/or international law firms in the USA and UK, drivers of change in the legal market, have created or changed their human resource (HR) department designations for TM (Mottershead, 2010), sparking a new trend. The identification, development and retention of the most talented lawyers have become a priority.

2.1 Performance appraisal in law firms

Appraisals are the cornerstone of TM. They enable differentiation of talent and support up the career model. Since the mid-nineteenth century, lawyers have been ranked against their peers during the whole course of their work in the firm, from admission to partnership

(Pinnington, 2011). Partners annually appraise lawyers in the same cohort (i.e. those with the same qualification year). The highest-performing lawyers advance to the next rung on the career ladder and receive the largest bonuses, while average and low-performing lawyers remain at the same professional level or are invited to leave, their replacements being vetted through the recruitment of trainees from elite law schools (Welch and Welch, 2005). This tournament was first introduced by the American law firm Cravath to create a continuous renewal of the workforce, supporting excellence and meritocratic policies.

Most firms have followed a TM approach that is focused on identifying and retaining high-performing lawyers. Accordingly, different percentages of the workforce are expected to perform at different levels (Welch and Welch, 2005). The professionalized HR departments have introduced additional and sophisticated practices to differentiate lawyers according to performance, using appraisal systems based on relative comparison, such as forced-distribution ranking systems. The distributions used are frequently adapted from the Gaussian curve, and lawyers are ranked into performance levels (e.g. 20 percent–70 percent–10 percent), talent levels, or the well-known designation of A, B and C players (Collins, 2001; Guest *et al.*, 2004; Ready *et al.*, 2010; Welch and Welch, 2005). Like the original tournament, force-ranking systems are instituted to improve the potential of the workforce (Scullen *et al.*, 2005).

Ranking systems are considered to have greater validity than other appraisal methods (e.g. Balzer and Sulsky, 1992; Chattopadhayay and Ghosh, 2012; Goffin *et al.*, 2009; Heneman, 1986; Nathan and Alexander, 1988; Wagner and Goffin, 1997). They are acknowledged to offer better prospects for differentiating individuals' performance, avoiding the frequent rating biases that prevent marked differentiation between individuals' performance, such as leniency (a tendency to over-evaluate performance, first described by Ford in 1931) and the halo effect (described by Thorndike in 1920, which reflects exaggerated correlations among ratings of disparate criteria) (McBriarty, 1988; Stewart and Nandkeolyar, 2006). Rankings find support in natural social-comparison processes (Wagner and Goffin, 1997) that underpin decision-making processes, such as appraisals. Scullion *et al.* (2000) confirmed that it is easier for managers to identify the contribution of each individual through comparison with peers.

Of course, ranking systems are not without their critics. On the contrary, they are consistently the target of fierce criticism, which, for instance, alleges discouragement of collaboration and communication as unintended consequences (Pfeffer and Sutton, 2006). The over evaluation of average performers integrated in low-performing teams and the under-evaluation of high performers integrated in high-performing teams have also been reported (O'Boyle and Aguinis, 2012).

Criticism is not exclusively brought to bear at ranking systems. Performance appraisal is both the most widely used (Guest *et al.*, 2004) and the most disliked TM practice (Aguinis *et al.*, 2012). Its cost in effort and wasted time, as well as the negative impact on team cohesion, are commonly criticized (Lawler *et al.*, 2012). Most individuals believe that they perform above average (Sharot *et al.*, 2011), so rankings lead to dissatisfaction and feelings of injustice among those ranked at average and lower levels, as well as to difficult conversations with partners, who would prefer to avoid managing negative impacts on interpersonal relationships (Bol, 2011).

Performance appraisal is, however, a powerful TM practice (Chattopadhayay and Ghosh, 2012; Judges and Ferris, 1993; Murphy and Cleveland, 1995), which is required to effectively manage talent (Lawler *et al.*, 2012). It is the annual rite of appraising that "triggers dread and apprehension in the most experienced, battle-hardened manager" (Roberts and Pregitzer, 2007, p. 15). In response of criticism of annual rankings, Allen & Overy, Hogan Lovells and Slaughter and May, which are three of the largest law firms in London and role models for other firms, recently announced the replacement of yearly rankings with other forms of feedback (Simmons, 2017). The time and effort spent on making rankings to identify talent may have been leaving scarce energy for talent development.

2.2 Competency frameworks in law firms

To support TM, law firms have implemented competency frameworks that are drawn from high-performers' profiles (Mottershead, 2010; Polden, 2012), which describe the range of skills required for career success. Hard (i.e. legal) and soft skills (i.e. managerial) are given behavioral descriptions. Legal knowledge is a primary requisite (Bock and Berman, 2011; Polden, 2012) at the base of such hard skills as oral advocacy, drafting, analysis and problem solving. Lawyers are also required to display soft skills related to teamwork, efficiency management, client relationships, business development and coaching (Bock and Berman, 2011; Mottershead, 2010; Polden, 2012; Stumpf, 2007).

Competency frameworks form criteria for TM, from recruitment to appraisals. The development of lawyers requires in-depth feedback, taking all the skills of the competency framework into full consideration. On the contrary, performance rankings result from a comparison between lawyers' overall performance (Lopes, 2016).

3. Performance rankings prediction

Prediction is a critical form of knowledge about indeterminate or anticipated events. It is essential for making decisions in the present that will have impact in the future (Jantan *et al.*, 2009). Within organizations, performance prediction is vital for forecasting purposes and central to forming TM strategies (Cascio and Aguinis, 2011; Hinds *et al.*, 2000; Mehrabad *et al.*, 2011; Sonnentag and Frese, 2012). However, few studies exist on performance prediction. Prediction models intended to support practitioners by talent forecasting have thus far been a mirage, and law firms are no exception. Law firms attempt to identify the most talented trainees directly out of law school. Recruitment is supported by assessment tools, such as ability tests and personality questionnaires, which have demonstrated validity to predict performance over time (Tziner *et al.*, 1993). Following their admission into a firm, however, it is a struggle to identify high performers. Time and effort are spent in creating annual rankings of lawyers according to performance differentiation, jeopardizing investments in feedback and development.

Multivariate models, such as ordinary least squares, that estimate parameters in a linear regression mode are the most common approach to prediction in TM seen in the few studies available. However, linear models fail to uncover non-linear patterns. For data that do not fit parametric assumptions (e.g. rankings of performance), noisy and missing data (in consequence, e.g., of turnover over time, which is common in law firms), and with longitudinal samples including over 100 cases, such this study, linear models are not appropriate (Klimasauskas, 1991; Scarborough and Somers, 2006). ANNs may be a suitable option for overcoming the identified constraints, as they have demonstrated superiority to regression analysis for the purposes of prediction in comparability studies (e.g. Caudill, 1991; Mehrabad *et al.*, 2011; Noorossana *et al.*, 2009).

ANNs are a class of mathematical methods used to reproduce some aspects of brain functioning (Anderson, 1995). ANNs are classified among machine learning methods and have been designed to serve multiple purposes, ranging from pattern recognition (e.g. deep learning) to signal processing, noise cancellation, classification, forecasting and prediction. Scarborough and Somers (2006) found that ANNs have allowed the solution of several problems in different fields related to prediction that had previously been considered unanswerable. Hussain (1999) noted several applications, ranging from weather forecasting, compression of large data sets (e.g. big data), modeling of biological systems, pattern recognition in medical diagnosis and applications within the field of psychology (e.g. Levine, 1989; Starzomska, 2003).

ANNs have been misused in TM (Chandrasekar *et al.*, 2015; Scarborough and Somers, 2006; Wong *et al.*, 2000). Their rare application has been in the field of classification and for confirmatory purposes. For instance, ANNs have been successfully used to uncover non-linear relationships between satisfaction and performance (Somers, 2001), between satisfaction and commitment (Chandrasekar *et al.*, 2015) and between tenure and turnover (Seitz *et al.*, 2000); which linear models failed to explain (Chandrasekar *et al.*, 2015; Huang, 2012; Scarborough and Somers, 2006). For prediction purposes, their application has been limited. Employee selection for recruitment purposes (e.g. Mathuriya and Bansal, 2012) and turnover modeling (e.g. Sexton *et al.*, 2005) are the most common applications found in the literature.

To our knowledge, ANNs have never addressed performance rankings, either in law firms or in other settings. Schmidt *et al.* (1988) identified trends in high and low performers over time, pointing the way to an avenue for research in prediction that has not yet been pursued, although 30 years have gone by. We propose an ANN for prediction of performance rankings over time to fill this gap.

3.1 Performance rankings predictors

ANNs are machine learning methods and, like the brain, learn from experience. However, they do not precisely mimic biological neural networks. They are mathematical, data-driven processes, highly dependent on the nature and quality of their data for the learning they exhibit. Therefore, in the case under discussion, ANNs used to predict performance rankings, the learning mechanism is no less highly dependent on the inputs, the predictors (Jin and Gupta, 1999).

This work proposes an ANN that learns trends from past performance rankings to predict performance rankings over time. Past performance is known to be the most powerful predictor of future performance (Sturman *et al.*, 2005; Sturman, 2007). The first predictor incorporated into the model is past performance rankings. There are recent studies that show performance trends over time (e.g. Berrah *et al.*, 2006; Devaraj *et al.*, 2004; Hua Tan *et al.*, 2004; Unahabhokha *et al.*, 2007) and profuse literature demonstrating that performance is sufficiently stable to be predicted (Hofmann *et al.*, 1992, 1993; Sonnentag and Frese, 2012; Stewart and Nandkeolyar, 2006; Thoresen *et al.*, 2004).

Performance includes both stability and dynamism (i.e. lack of stability). This is because performance is underlined by attributes that remain stable over a lifetime, such as cognitive ability and personality, and it is influenced by knowledge, experience (Schmidt *et al.*, 1986; Sturman, 2003) and motivation (Kanfer, 1992), which shift and lead to performance dynamism. Studies have shown that the predictive validity of measures of performance decreases over time, due to the dynamic dimension of performance (Austin *et al.*, 1989; Barrett *et al.*, 1989; Ployhart and Hakel, 1998; Rambo *et al.*, 1983), but the correlation over any period has been found to remain positive, pointing to a stable dimension (Ackerman, 1987; Henry and Hulin, 1987; Murphy, 1989). Considering meta-analytic results for appraisals, Sturman *et al.* (2005) showed performance stability over a one-year period, ranging correlations from 0.85 to 0.67. Alessandri and Borgogni (2015) also found a large degree of performance stability over a four-year period.

Knowledge, experience and motivation vary according to the phase of a lawyer's career. Murphy's (1989) and Kanfer and Ackerman's (1989) models show that performance follows a steep learning curve during the learning phase. Baltes and Baltes's (1990) theory of selection, optimization and compensation corroborates the idea that younger individuals devote more resources to their work at the beginning of their careers, then entering a maintenance phase, during which their learning curve becomes shallower. This also applies to newcomers in a law firm. Through their careers, lawyers are in either a learning, developmental or growth phase (junior lawyers and newcomers) or a maintenance phase (middle and senior lawyers, and those with greater tenure). Two variables that are related to learning phase are included in the model proposed in this work: professional level and tenure. These variables, related to chronological time, are of relevance in longitudinal studies (Harris *et al.*, 2006) and are frequently integrated in studies of performance (Ackerman, 1992; Farrell and McDaniel, 2001; Tesluk and Jacobs, 1998). Lawyers are sorted into professional levels according to their years of experience following passing the bar exam, it is related to experience and age. Tenure relates to experience and age because many lawyers develop their careers within the confines of one law firm. However, recently, an increasing number of lawyers have begun to make career transitions between firms.

The fourth and last variable to be learned by the ANN is billable hours. Each lawyer has an annual target of working hours to be billed to clients. Billable hours represent the most common fee arrangement in law firms. Timesheets are used to charge clients for time spent on different matters, broken down into short time intervals, with amounts per hour defined according to the seniority of the given lawyer (Campbell *et al.*, 2012). The number of billed hours accumulated by a lawyer contributes directly to the financial performance of the firm. To incentivize billing hours, accomplishments are a frequent criterion for bonuses (Campbell *et al.*, 2012; Mottershead, 2010). Lopes *et al.* (2015) found a marked positive correlation between the number of billable hours and appraisal ratings.

In this study, we use an ANN as an exploratory tool, following Scarborough and Somers's (2006) proposal. Instead of using an ANN in a confirmatory way to confirm a linear hypothesis, the full range of possible relationships among the four imputed variables is explored. A 70 percent rate of correct prediction is fair performance by an ANN, according to the literature (Adefowoju and Osofisan, 2004; Emuoyibofarhe *et al.*, 2003; Oladokun *et al.*, 2008). We expect our model to attain that degree of accuracy. As has been found, we expect prediction accuracy to decrease as the simulation extends over a longer period of time (Austin *et al.*, 1989; Barrett *et al.*, 1985, 1989; Hagan *et al.*, 2014; Ployhart and Hakel, 1998; Rambo *et al.*, 1983).

4. Methods

4.1 Setting and data

In 2016, data were drawn from a large Portuguese law firm. Variables for individual differences and performance rankings were collected from the administrative records of the firm. All 140 lawyers appraised between 2008 and 2015 were included in the study (Table I). In 2008, the competency framework used by the firm to conduct the appraisals was revised.

	Appraisals per year							
	2008	2009	2010	2011	2012	2013	2014	2015
Performance ranking								
Low performance	7	11	12	4	2	1	2	2
Average performance	29	30	30	36	37	34	43	38
High performance	23	26	25	22	23	26	27	26
Very high performance	11	13	14	12	18	22	20	15
Total	70	80	81	74	80	83	92	81
Professional level								
Junior	16	15	16	14	16	11	13	8
Middle	34	38	32	29	24	30	35	26
Senior	20	27	33	31	40	42	44	47
Tenure								
< 2 years	20	9	8	9	12	10	17	1
2–3 years	17	29	23	11	13	16	14	18
4–5 years	10	15	18	25	18	11	16	16
⩾6 years	23	27	32	29	37	46	45	46

Note: $n = 140$

Table I.
Performance appraisal sample demographics

Between 2008 and 2015 the new competency framework was used for the appraisals and performance rankings. Although additional partners did join the partnership throughout the eight-year period of study, the head of each practice, who was responsible for appraisals within that practice, did not change.

4.2 Measures

4.2.1 Performance rankings. The performance rankings in this firm result from appraisals. A two-step approach is followed, first appraising and then ranking lawyers' performance. This procedure is common in law firms and organizations in various industries that invest in TM (Welch and Welch, 2005). First, each year, including the eight years of this study, the performance of each lawyer is rated by the partners, using a competency framework, including hard skills (i.e. knowledge and solutions, communication and drafting and client orientation) and soft skills (i.e. business development, firm focus, leadership, resource management and achievement focus). The ratings for each skill are calculated by averaging sub-items using a five-point, behavioral-observation rating scale (Christ and Boice, 2009), anchored by behavior frequency. The overall appraisal ratings for each lawyer are computed by averaging all ratings of evaluated skills, in each of the eight years.

Second, the overall appraisal ratings of the lawyers are ranked according to the professional level (i.e. each lawyer's performance was compared against peers at the same professional level: junior, middle and senior). Based on a pre-defined distribution adapted from the Gaussian curve (5 percent–25 percent–50 percent–20 percent), lawyers are placed, for each of the eight years, into four performance groups (1–4): 1 = low performance, 2 = average performance, 3 = high performance and 4 = very high performance.

4.2.2 Billable hours. Billable hours are the number of hours worked and billed to clients by each lawyer. Lawyers have an annual target for billable hours. The percentage of accomplishment of that target for each of the eight years by each lawyer is integrated into the model.

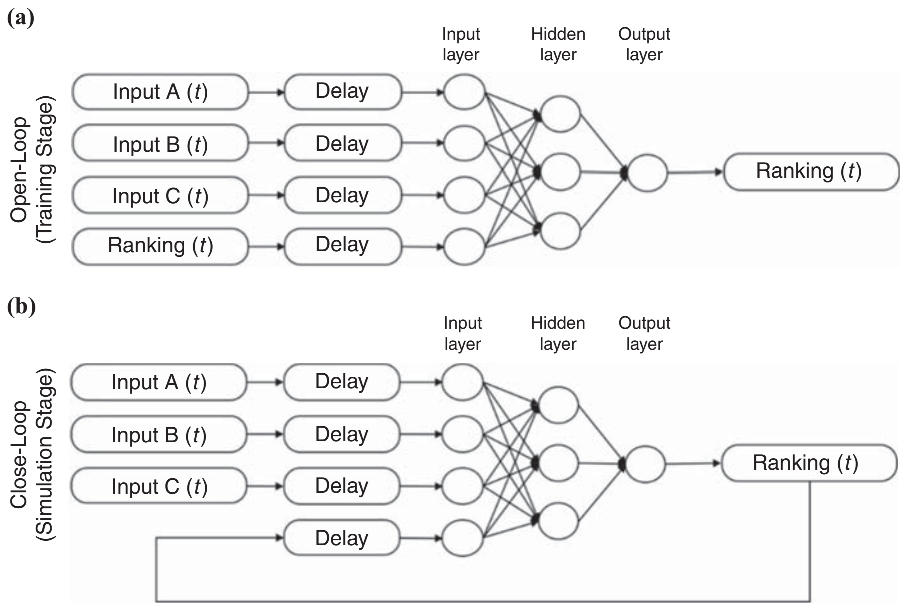
4.2.3 Professional level. The professional level ranges from junior = 1, to middle = 2 and senior = 3 levels. In the law firm, career progression is linked to both experience and performance. The number of years at each professional level varied for different individuals.

4.2.4 Organizational tenure. Tenure is calculated based on the date of admission to the firm, for each of the eight years of performance rankings.

4.3 Proposed predictive model

In this paper, an ANN termed a multilayer feedforward neural network is selected to assemble a mathematical model to predict of performance rankings. This type of ANN is characterized by a series of layers composed of nodes (or neurons). Because each layer's nodes are closely connected with those of the neighboring layers (the equivalent of brain synapses) information propagates through the network, generating outputs (Hagan *et al.*, 2014). This type of ANN is used to map a relation between two sets of data. One set of inputs is received and then translated into sets of corresponding outputs. Signs only flow in one direction (see Jin and Gupta, 1999).

ANNs operate in two stages: training and simulation. An ANN is trained using multiple examples (known data) of pairs of inputs/outputs (Figure 1(a)) and learns through experience. The training of an ANN is the process of adjusting its parameters to the empirical data given using a procedure and algorithm to make its predictions are as accurate as possible. This training is an iterative process that proceeds until one or more criteria are met (e.g. global error or maximum number of iterations). More details on data propagation and the training of feedforward ANNs can be found in Beale *et al.* (1992). After the end of the training process, the network can make predictions. This is known as



Notes: (a) Configuration for the training stage; (b) configuration for simulation/prediction

Figure 1. Example of a three layer NARX artificial neural networks (with three exogenous inputs and three hidden nodes) similar in structure to those included in this work

simulation mode. Our simulation begins from a known situation (Year 0). The performance ranking prediction for Year 1 is then used to estimate the Year 2 performance ranking, and so on. Simulation works in a closed-loop fashion (Figure 1(b)).

The application of an ANN to the prediction of lawyers' performance rankings using past performance rankings, professional level, tenure and billable hours requires a feedforward autoregressive non-linear dynamic process with exogenous inputs network. The autoregressive aspect of this process means that the prediction of future performance rankings depends on actual performance ranking. It must be non-linear because mapping between the inputs and performance ranking is complex and it is not possible to represent it using a combination of linear relations. It is dynamic because it represents a process that evolves over time. Finally, it accepts data from exogenous sources (in this case, professional level, tenure and billable hours) (Gupta *et al.*, 2004; Pearlmutter, 1990). The ANN must be supervised, meaning that the output should compare with the known correct values during training (Scarborough and Somers, 2006). A schematic representation is provided in Figure 1.

Our ANN combines professional level, tenure and billable hours with the most recent performance ranking and then predicts the subsequent performance ranking. It considers the initial performance ranking (1–4) as an input and performance ranking at each of the lag times as output. The occurrences for all lag times for all eight years of performance rankings are input. Network inputs are delayed to perform simulations with multiple time lags. For instance, different time periods (from one to six years) are taken into account when the ANN is built. The rarity of occurrences for the seven-year lag time precludes the performance of the simulation for that period. Because there are fewer occurrences and longer time, prediction accuracy is expected to decrease as the simulation extends over longer periods of time (Hagan *et al.*, 2014). Maximal accuracy is expected for the one-year lag time, and 496 occurrences over the eight years of performance rankings are considered.

The model is calibrated using data for approximately 70 percent of the lawyers in the database, and it is independently tested on the remaining 30 percent. An early-stopping training procedure is implemented to avoid overfitting. The networks architecture is standard three layer, with one input and one hidden (i.e. hyperbolic tangent function) and one output layer (i.e. linear function), according to Caudill's (1991) and Klimasauskas's (1991) recommendation. Both authors found that most problems can be solved with ANNs using three layers. The number of nodes in the hidden layer is optimized, using cross-validation. All calculations are performed with the neural network toolbox for MATLAB, version 8.6 (Beale *et al.*, 1992).

ANNs and multivariate models, which estimate parameters in a linear regression mode, can both be used for predictive purposes. Following a commonly reported practice (Somers, 2001) and a reviewer's suggestion, we compare the results obtained from the ANN with results obtained from a multiple linear regression analysis (MLR), which is the most common approach to prediction in the field of HR. Here, a linear autoregressive with exogenous inputs is used to compare with a non-linear ANN. The MLR model is built with single inputs (no interactions) for comparison purposes. The same variables (as used for the ANN) are input into the model: performance ranking in Year K, professional level, tenure and billable hours, and the output was change in rankings (ranking [Year K+dK]–ranking [Year K]), to mimic the ANN inputs. Delay dK varies between a one- and six-year lag time. For each data set (for each dK) cases are randomly split 70 percent/30 percent for training and testing. The model coefficients are estimated by ordinary least squares using the training set. The calibrated model is applied to the testing set. The presented results correspond to the predictions of the testing set.

Because performance comprises stability and dynamism, two testing conditions (both for ANNs and MLR) were set: one including all conditions (performance ranking maintenance and change, from one year to the next), and a dynamic condition including only performance ranking change from one year to the next).

5. Results

Prediction results for the ANN and the MLR are presented in Table II. Loss of predictive accuracy is always expected between training and testing (Scarborough and Somers, 2006), but for the networks developed in this work the loss is non-significant.

For a lag time of one year the ANN yields a 71 percent rate of correct predictions in conditions where performance ranking change, and it predicts about three out of four cases correctly (73 percent) when all conditions are included. With a two-year lag time, the prediction levels were 67 and 69 percent, respectively. Thus, the model was found optimal, as attested in the literature (Oladokun *et al.*, 2008). The accuracy of our network exceeds,

Table II. Summary of the predictions obtained for a dynamic feedforward neural networks resourcing (ANN), and for a linear autoregressive with exogenous inputs (MLR)

		Prediction lag time (years)					
		1	2	3	4	5	6
Input variable ID	Variable *N* occurrences	496	358	258	182	122	73
1	Tenure	++	+	+	0	−	−
2	Professional level	+	+	0	0	−	−
3	Billable hours	++	++	++	+	+	0
4	Performance ranking (year 0)	+++	+++	+++	+++	+++	+++
ANN Correct predictions (training/validation) (%)		74	71	66	65	64	58
ANN correct predictions all conditions (simulation) (%)		73	69	56	56	56	56
ANN correct predictions when ranking changes (simulation) (%)		71	67	62	63	63	57
MLR correct predictions all conditions (%)		72	66	48	48	48	48
MLR correct predictions when ranking changes (%)		56	41	23	23	23	23

Notes: Categorical symbols were assigned to the observed sensitivity, 0 poor relevance to +++ highly relevance; − non-relevant for example, Chandrasekar *et al.*'s (2015) 64.1 percent network accuracy (in the context of classifying employees according to satisfaction).

As expected, the accuracy level decreases over time. With a three-year lag time, the prediction level of the network decreases to about 62 percent when ranking changes and to 56 percent when all conditions are considered, which is a non-significant result, similar to random chance (for which one can expect a 50 percent accuracy).

The initial performance rankings is the most relevant input for the network at all lag times, which is in line with the literature (Sturman *et al.*, 2005; Sturman, 2007). The other three predictors, in terms of decreasing importance, are billable hours, tenure and professional level.

For comparative purposes, an MLR was performed. For all conditions, the difference of results from that of the ANN is non-significant. But under the dynamic condition the MLR is unable to find an accurate prediction. With a one-year lag time, for instance, the results do not significantly outperform random prediction (56 percent).

6. Discussion

Law firms emphasize TM to ensure long-term sustainability, but this goal remains far from being achieved. More sophisticated practices are in use, such as assessment tools for recruitment purposes, competency frameworks and forced-distribution ranking systems, but the annual rite of ranking lawyers to identify high performers and support career decision making persists. Appraisal and rankings, which are the least popular TM processes (Aguinis *et al.*, 2012), are repeated year after year, monopolizing time and effort and, sometimes, damaging good relationships between partners and lawyers.

In line with the law firm career model, the priority of identifying the most talented lawyers is dominant. The performance ranking of lawyers is unduly valued, over and above their ratings in each of the skills of the competency framework. Therefore, feedback that could support lawyers preparing for their increasingly daunting tasks in the new economic reality may be precluded. According to Nelson (1981), partners are the firm finders (business developers), minders (managers) and grinders (producers). Their time is scarce. Prediction could allow for greater spare time to be reinvested in providing feedback and supporting career development.

This study pioneers performance prediction for TM in law firms. Prediction is commonplace in engineering but infrequent in HR field (Jantan *et al.*, 2009). Predictive models are much less accurate in the behavioral science than they are in engineering because human behavior is difficult to measure reliably (Scarborough and Somers, 2006). This may underline the lack of attention that has come from the field and the lack of predictive models to support practitioners. We intend to fill the gap by proposing an ANN that learns from input data (namely, initial performance ranking, billable hours, professional level and tenure) and predicts performance rankings over time.

ANNs are a model of choice when parametric assumptions are not met, when noisy data exist, or longitudinal data with over than 100 cases form the set, as is the case in this work (Klimasauskas, 1991). In fact, ANNs overcome the limitations of MLR and generate more accurate results (see Collins and Clark, 1993; Sharda and Patil, 1992; Somers, 2001, for reviews). MLR were able to predict when all conditions (performance ranking maintenance and change) were considered, but did not overcome a random prediction in the condition of ranking change. This may result from more accuracy predicting stability over time that future studies should verify.

The relevance of tenure and professional level to the model supports a likely different trend of performance during the learning phase, as suggested by the learning theories of Murphy (1989), and Kanfer and Ackerman (1989). The motivation to thrive early in one's career (Baltes and Baltes, 1990) might also play a role in the improvement of performance among junior lawyers. Billable hours outweigh even professional level and tenure in importance for performance ranking predictions. Increases in performance ranking were shown to be linked with increases in billable hours, and the reverse was also true. This evidence is in accordance with Lopes *et al.*'s (2015) findings, which were related to a strong correlation between the number of billable hours and appraisal ratings. High-performing lawyers produce more billable hours because clients and partners solicit them more often.

Implications for implementation in law firms can be drawn. We suggest that predictive models, such as the model proposed in this paper, could have prevented situations such as the complete abandonment of performance rankings by Allen & Overy, Hogan Lovells and Slaughter and May. This is a recent trend, initiated by some audit and consulting firms that do not stress rankings for the identification of the most talented individuals, although this is required to thrive in fast-changing markets (Ashton and Morton, 2005; Buckingham and Vosburgh, 2001; Dries, 2009; Sengupta, 2012).

We argue that appraisals and performance rankings should continue in law firms. First, performance rankings are linked to a meritocratic system that sends a message of quality to the clients and the market, creating a competence allure (Greenwood, 2003). Second, rankings support the generally accepted career model, which has been successful in driving profitability. Competition among lawyers to reach the top boosts their motivation to produce large numbers of billable hours without the necessity of complex managerial and control processes (Galanter and Palay, 1990, 1994). Third, this widely applied HR practice (Guest *et al.*, 2004) enables the differentiation of high, average and low performers, which is critical for managing talent. Fourth, ranking systems have increasingly demonstrated their greater validity than other appraisal methods for differentiation purposes (Chattopadhayay and Ghosh, 2012). Fifth, communicating rankings to lawyers helps to create a culture of transparency, as benchmarking become possible. Sixth and last, the model adjustment allows for the prediction of up to two-year lag times. Thus, regular rankings are still needed.

But for two years, instead of spending time completing predictable performance rankings, partners might benefit from additional time spent developing lawyers. The promotion of lawyers' awareness, through feedback in relation of each appraisal criterion, as well as preparing lawyers for additional challenges along their career paths, is of much greater importance than ranking performance annually.

An important application of an ANN would be in the field of strategic planning. HR practitioners could benefit from forecasting talent to better allocate resources. The earlier signposting of lawyers whose performance rankings are likely to change would allow a closer career examination, for example.

One final application rests in the possibility to identify the most talented, highest-performing lawyers early in their careers. This major possibility has the potential to influence the career model. A talented lawyer can be identified early and might benefit from support for development, including skills required for future managerial roles.

6.1 Limitations and future research

A first limitation stems from the data set, which was gathered exclusively from only one firm, which precludes any generalization of results because of common method variance, which influences contextual factors in measures that cause systematic covariation (Podsakoff *et al.*, 2003). Thus, replication study with additional firms is necessary for any generalization to be meaningful. Broader samples are also required to address the second limitation: high turnover in the sample. Turnover is greatest for knowledge workers, such as lawyers, among all types of professions (Somaya and Williamson, 2008), causing range restrictions for the analysis of performance over time (Goodman and Blum, 1996; Schmidt and Hunter, 2004; Sturman and Trevor, 2001). For this reason, correlations among variables might be reduced in our results (Sackett and Yang, 2003; Schmidt and Hunter, 2004).

Analysis is conducted for all occurrences at lag times, which allows for overcoming the frequent limitations of the analysis of only cases with complete data. However, as lag times increase, the occurrences that fed the network decrease, from 496 when the lag was 1 year to 32 when it was 7, precluding, for instance, the analysis of the final lag. Network training becomes progressively less effective and errors increase, not just because prediction was more difficult over a longer horizon but because there are fewer occurrences to train the network.

During the period of analysis, lawyers advance in their careers. One input in the predictive model is the professional level, which revealed itself to be an important predictor. As a reviewer stressed, some validity issues are raised by career advancement; we note these and future studies should address them.

Another limitation results from the biases affecting performance rankings (Bol, 2011), which are well-known but impossible to control in longitudinal studies. The predictive model is trained to predict performance rankings, and it learned the rater biases, which were replicated. A post-evaluation of the ANN by the raters was out of the scope of this work. The analysis of time and effort that ANN may reduce is must be pursued in future research. Additionally, the satisfaction of lawyers, partners and HR practitioners is important for future evaluations.

Because no widely accepted theory for the design of networks is available, decisions on training, the number of hidden layers and nodes and training adjustments for increasing accuracy must be conducted by trial and error. Thus, different and better networks can be designed (Naik and Ragothaman, 2004).

One topic that is worth investigating relates to additional predictors that may increase the accuracy of the predictive model. ANNs that consider different professional levels and tenures should also be explored. This might allow for more accurate predictions over time. Firms, in this scenario, would not need to wait for the full evolution of a lawyer's career to identify a tournament winner. New career architectures following different performance ranking trends are a final topic for future research. TM requires that talent be managed for the long term (Boudreau and Ramstad, 2005), and ANNs allow "looking at long-standing problems in new ways" (Scarborough and Somers, 2006, p. 46).

6.2 Conclusion

It is time consuming and troublesome to rank all lawyers against peers. This burden of this practice, however, can be alleviated by the predictive use of ANNs. This paper employed methods beyond the traditional static study of performance, including non-linear modeling for prediction. The study tested an ANN's prediction of performance rankings that is adjusted until two-year lag time. The superiority of the ANN over an MLR model was tested and confirmed. The time freed can be invested in strategic planning, lawyers' feedback to raise awareness and talent development for readiness in the turmoil of the new millennium.

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About the authors

Susana Almeida Lopes received the Psychology Degree from Coimbra University, with specializations in Work and Organizational Psychology, and Clinical Psychology (2000); the PhD Degree in Organizational Psychology from Lisbon University (2017); and post graduations on Applied Quantitative Methods from ISCTE (2002), Law Firm Management from Porto Business School (2010), and on Strategic HR Practices from Cornell University (2010). SAL is currently a member of the Research Center for the Psychological Science of the Lisbon University. She started her career at SHL, where she advanced from Trainee to Managing Consultant. She is currently the Organizational Director at VdA, where she addresses strategic HR planning, talent management, competency model, appraisal system, career management, reward, development and recruitment. She directs the HR analytics research projects at VdA Legal Analytics Bureau. SAL is a member of the board of the Order of Psychologist in Portugal, since 2016. She was awarded several times for talent management innovative projects and ranked among the most innovative individuals by *Financial Times* in 2014. Susana Almeida Lopes is the corresponding author and can be contacted at: sal@vda.pt

Maria Eduarda Duarte is Full Professor at the University of Lisbon, Faculty of Psychology, where she directs the Master Course in Psychology of Human Resources, Work and Organizations. Her professional interests include career psychology theory and research, with special emphasis on issues relevant to adults and the world of work. Her publications and presentations have encompassed topics on adult's career problems, testing and assessment and counseling process. She was Chair of the Portuguese Psychological Society (2005–2018); she also served on editorial boards for some Portuguese, European and Iberia-American journals. She was the Director of the National Institute of Guidance (2009–2014). She is President of Counseling Division (2014–2018), IAAP. She is President of UNESCO CHAIR – Lifelong guidance and counseling, University of Wroclaw. She is Fellow Award – IAAP (2014), and ESVDC award 2015. She is also National Defence Adviser, since 2007.

João Almeida Lopes received the BSc/MSc Degree in Chemical Engineering in 1997 at the Technical University of Lisbon, and the PhD Degree in Pharmaceutical Engineering in 2001. Until 2005 he was a Postdoctoral Researcher at the same University and Consultant for the pharmaceutical industry.

In 2006, he joined the University of Porto as Assistant Researcher in the areas of green chemistry, chemometrics and process spectroscopy. He created the Chemometrics and Process Analytical Technology research group being its coordinator since then. He founded Worldmetrics Solutions, a consulting company providing technology solutions for high-throughput industrial processes monitoring. He has been Assistant Professor of Pharmaceutics at the Faculty of Pharmacy, University of Lisbon since 2014. JAL published more than 100 scientific articles, coordinated more than 40 R&D projects and supervised circa 90 students and researchers (MSc, PhD, Postdoc levels). He was the President of the Portuguese Association of Researchers in Science and Technology (2012–2014) and currently General Assembly President, Vice-President of the Portuguese Society of Pharmaceutical Sciences (from 2017), appointed President of the Analytical Chemistry division of the Portuguese Society of Chemistry (from 2019), member of the steering committee of the QbD/PAT network of the European Federation for Pharmaceutical Sciences (from 2011) and the Voice of Researchers initiative of the European Commission (2010–2016). He is Scientific Consultant in Process Systems Engineering, Process Analytics and Pharmaceutical Development for several industrial companies.