

ANTICIPATING THE DURATION OF PUBLIC ADMINISTRATION EMPLOYEES' FUTURE ABSENCES

Leandro Costa

MsC in Computer Science and Business Management,
Instituto Universitário de Lisboa, Lisboa, Portugal
Address: Av.^a das Forças Armadas, 1649-026 Lisboa.
E-mail: leandro.mbccosta@gmail.com

Ricardo Filipe Ramos

PhD, Assistant Professor at Universidade Autónoma,
Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR-IUL, Lisboa, Portugal;
CICEE – Centro de Investigação em Ciências Económicas e Empresariais,
Universidade Autónoma de Lisboa, Portugal.
Address: Av.^a das Forças Armadas, 1649-026 Lisboa.
E-mail: ricardo_ramos@iscte.pt

Sérgio Moro

PhD, Sub-Director of ISTAR-IUL, Assistant Professor at ISCTE-IUL,
Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR-IUL, Lisboa, Portugal.
Address: Av.^a das Forças Armadas, 1649-026 Lisboa.
E-mail: scmoro@gmail.com

Abstract

Absenteeism affects state-owned companies who are obliged to undertake strategies to prevent it, be efficient and conduct effective human resource (HR) management. This paper aims to understand the reasons for Public Administration Employees' (PAE) absenteeism and predict future employee absences. Data from 17,600 PAE from seven public databases regarding their 2016 absences was collected, and the Recency, Frequency and Monetary (RFM) and Support Vector Machine (SVM) algorithm was used for modeling the absence duration, backed up with a 10-fold cross-validation scheme. Results revealed that the worker profile is less relevant than the absence characteristics. The most concerning employee profile was uncovered, and a set of scenarios is provided regarding the expected days of absence in the future for each scenario. The veracity of the absence motives could not be proven and thus are totally reliable. In addition, the number of records of one absence day was disproportionate to the other records. The findings are of value to the Human Capital Management department in order to support their decisions regarding the allocation of workers and productivity management and use these valuable insights in the recruitment process. Until now, little has been known concerning the characteristics that affect PAE absenteeism, therefore enriching the necessity for further understanding of this matter in this particular.

Keywords: absenteeism; human resources; public administration; data mining.

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Introduction

An employee is absent when they are not present in the workplace during their regular work schedule. If a worker has more than one absence, then the non-appearance durations are totaled, respectively, to determine the absence period (Zatzick & Iverson, 2011).

Managing absenteeism is critical for any type of company (Zheng & Lamond, 2009). Recent research on causes of absenteeism has unveiled individual characteristics such as personal issues (e.g., illness, stress) (Edwards, 2014; Mudaly & Nkosi, 2015) or external reasons (e.g., family, grievances) (Hebdon & Noh, 2013; Vignoli *et al.*, 2016), with the subsequent effect of the absences being difficult for the HR department to manage. As a result, absenteeism inevitably provokes damage in any Public Administration, so it must be understood and controlled in order to prevent flaws in the process, achieve high levels of job satisfaction and turn it into increased productivity (Papavasili *et al.*, 2019) and, ultimately, efficiency. In this domain, Public Administration is considered an institution that has a large number of employees (Koprić, 2019) and, for this reason, potentially has more absent employees. Taking the example of Portugal, there are over 350 thousand workers in Public Administration, which, in 2017, had a 10.47% absenteeism rate (Estatística, 2018).

There is research on HR management (Armstrong, 2014), absenteeism (Schaufeli, Bakker and van Rhenen, 2009) and the public sector (Carvalho & Bruckmann, 2014; Leontjeva & Trufanova, 2018) as well as studies on data mining (Mergel, Rethemeyer & Isett, 2016) and its application in various contexts (Johnston, 2010; Romero & Ventura, 2013; Moro, Rita & Vala, 2016). However, there is a lack of studies about predicting employee absenteeism in Public Administration. Consequently, this study aims to fill this gap by characterizing PAE absenteeism through analyzing the worker profiles, the motives behind absence, the workers' absenteeism history and job specifics all of which will, in turn, enable us to predict future absences and the reasons for such absences. In January 2017, information concerning the 2016 absences of 17,600 PAE was collected from seven Portuguese public databases.

For the data analysis, RFM methodology was used to add variables to this complex issue, and a SVM for modeling the absence duration. Understanding the reasons that explain the duration of the upcoming absence of a public employee will make a conceptual addition to academia. Additionally, the development of a model to predict the duration of future absences can help HR managers in Public Administration to devise strategies to mitigate such absences accordingly, thus helping in better serving the public.

Theory

Human resources and absenteeism

Employee absences are both costly and disruptive for Public Administration, and the trend has been increasing steadily over the years (Hassan, Wright & Yukl, 2014). Personal illness and family assistance are considered as the main reason for unplanned absences, however, age, bereavement, and disability, all take a toll on the worker, which in turn affects morale, absences and productivity in the workplace (Kocakülâh *et al.*, 2016; Jong, 2018). However, Public Administration institutions have been attempting to determine the validity of these illnesses, along with incentives and possible solutions to mitigate these absences, including those caused by family issues. Effectively, previous findings have revealed that employees usually fake illness or sickness to be able to perform personal affairs (Hughes & Bozionelos, 2007) and detecting the veracity of any justification has been one of the challenges of employers (Beil-Hildebrand, 1996).

Effectively, absenteeism has a large effect either directly or indirectly on a Public Administration's bottom line. The costs associated with absenteeism are significant when everything involved is considered. One cannot look at just what it costs to replace the employee for a day. It is necessary to look at what it is going to cost to lighten the load and attempt to attack these ongoing ever-increasing problems in the workplace. One also has to look at the increase in corporate health benefit costs that will result if a hands-off policy is adopted and absenteeism is not taken seriously (Quinley, 2003).

Since every PAE is different, it will require various levels of analyses to identify the factors that impact absenteeism for a specific employer. If absenteeism is identified as a significant problem, the Public Administration will need to take a hard look at the cause of the problem and begin to consider strategies to recapture lost revenues. Furthermore, as the economy tightens and the related financial stress increases for most employees, it is very likely that employers may see an increase in absenteeism due to financial stress related issues. The more aware a company is of issues related to employee absenteeism, the more successful they will be in implementing strategies to reduce the related cost and increase productivity (Kocakülâh *et al.*, 2016).

Specific factors related to the employee absenteeism in the public sector

There is a positive correlation between age and absenteeism in the Public Administration. In fact, employees belonging to the X generation have higher rates of avoidable absence. On the other hand, Baby Boomers reveal lower rates of avoidable absence (Jurkiewicz, 2000). PAE age also has an influence on their health, affecting absenteeism. Being part of the older group of workers constitutes a moderated risk factor in terms of belonging to the sick list, which is backed up by other reports (Bastos, Saraiva & Saraiva, 2016; Sundstrup *et al.*, 2018). Age and motivation in the public sector are also related. Older PAE desire job security, monetary compensation and job flexibility in order to feel motivated (Bright, 2010). A less motivated employee leads to absenteeism (Rousseau & Aubé, 2013).

Although vacations are not considered to be an absence, they alleviate perceived PAE job stress and thus also the experience of burnout. Absenteeism for

non-health reasons decreased after a vacation, which implies that taking a vacation can be regarded as a stress management technique (Westman & Etzion, 2001). As such, it corroborates findings concerning the beneficial effects of stress management intervention on burnout and absenteeism.

The disability community is large, including not only people in wheelchairs, but also people with other mobility issues, people with varying levels of vision, speech, or hearing impairments and people with cognitive disabilities such as Down's Syndrome (Preiser, Vischer & White, 2018). Depressive and anxiety disorders are also mentioned as important drivers of work disability and absenteeism (Hendriks *et al.*, 2015), which is backed up by other authors (Ahola *et al.*, 2011; Alonso *et al.*, 2011; De Graaf *et al.*, 2012).

In order to prevent long-term work employee disability and absenteeism in Public Administration, more attention should be paid to the work environment (Nguyen, Dang & Nguyen, 2015), offering preventive interventions for early support and practices to appoint alarm signals at workplaces, promoting a way of early recognition of reduced work ability and mental health problems (Hendriks *et al.*, 2015).

Unplanned absences

Unplanned absences occur whenever PAE fail to be present during their scheduled work hours, often with no previous notification (Easton, 2011). In about 60% of absences, PAE either notified their supervisor in the morning of the absence or did not provide any notification. Furthermore, they concluded that unplanned absences disrupt workflow and reduce productivity, mainly because supervisors could not establish a plan for those absences in time (Salehi Sichani, Lee & Robinson Fayek, 2011).

However, unplanned absences and strategies to recover from them were subject of analysis (Easton & Goodale, 2005). Results concluded that the reduction in total profits due to absenteeism is strongly influenced by the staffing strategies and absence recovery policies that firms adopt to cope with absenteeism. Forty-hour working weeks and zero anticipated absenteeism with holdover absence recovery appears to be a robust combination, on average reclaiming nearly 60% of the profit consumed by unchecked absenteeism. For firms unwilling or unable to implement active absence recovery policies, planned overtime staffing strategies with absence anticipation appear less vulnerable to absenteeism.

Stress is one other reason for absenteeism in the Public Administration (Shoaib, Mujtaba & Awan, 2018). Employees who are suffering from stress at work are less likely to be productive (Lewis, Megicks & Jones, 2017). The causes of stress, or stressors, are numerous and can be found anywhere in the workplace. Psychosocial work stressors such as role ambiguity, role conflict, job design, supervisory behavior, and job insecurity have all been implicated as causes of work stress-related anxiety and depressive illness (Bakotić & Tomislav, 2013; Bowling *et al.*, 2017; Lewis, Megicks & Jones, 2017). Furthermore, stress at work also can lead to physical illness, psychological distress and illness, and sickness absence, invariably leading to absenteeism (Jordan *et al.*, 2003; Molines, Sanséau & Adamovic, 2017).

Stress, depression, or anxiety accounts for 46% of days lost due to illness (Cooper, 2008), and are the single largest cause of all absences attributed to work-related illness. Likewise, stress can lead to seeking alternate PAE, which demands Public Administration resources in the form of recruitment and training. In turn, stress can overburden Public Administration co-workers with additional responsibilities. This can lead to a heavier workload for already distraught employees, which affects their health and eventually results in even more absenteeism (Haswell, 2003).

Organizational restructuring was conducted by one Italian Public Administration in order to reduce sick leave compensation, by increasing the monitoring of the health status of absent employees in the public sector, conducted to a PAE behavioral change before its effective implementation (De Paola, Scoppa and Pupo, 2014). Effectively, it was discovered that the probability of workers taking days off work for sick leave decreased strongly (the estimated effect was of about 53%) once the reform was effectively implemented (Ibid.). The authors also found that absence behavior is responsive to wage reductions and changes in monitoring intensity.

Cuts in statutory sick pay in Public Administration do not significantly affect the incidence of long-term absenteeism. PAE do not significantly adjust their long-term sick leave behavior on the decision to enter an episode of long-term sick leave, however, the effects on the decision to reduce the length of the long-term sick leave episodes produced positive effects in middle-aged employees working full-time, reducing the length of absences significantly (Ziebarth, 2013). However, long-term sickness absences decrease activity and increase social isolation, making PAE have doubts concerning their own competence, increasing the probability of them not returning to work (Vlasveld *et al.*, 2012).

Family assistance also plays a crucial role in absenteeism. Balancing work and family life can affect absenteeism and job satisfaction (Anafarta, 2011; Vignoli *et al.*, 2016; AlAzzam, AbuAlRub & Nazzal, 2017). Childcare is a major issue that affects absenteeism. When combining job and family responsibilities, it implies role-overload and conflict leading to health problems, and, therefore, higher sickness absence (Bekker, Croon & Bressers, 2005).

Resources and support are an important motivational role and fulfill human needs such as relatedness and autonomy (Bakker, Demerouti & Schaufeli, 2005). Furthermore, the instrumental support that workers receive on one domain may free the necessary resources to be fully engaged in other roles, bringing fulfillment and satisfaction to the worker. Hence, family-related instrumental support has proven to mitigate absenteeism (Diestel, Wegge & Schmidt, 2014; Moraes & Teixeira, 2017). It was also found that employees who were more satisfied with the quality of their child's care experienced less work-family conflicts had less work absences (Payne, Cook & Diaz, 2012).

Loss, trauma, and grief are feelings associated with bereavement. This is a sentimental process that occurs when someone experiences a loss of great emotional importance (Foster & Woodthorpe, 2016). Absence due to bereavement leave has an impact on productivity losses and the economic effects are substantial (Fox, Cacciatore & Lacasse, 2014). Overall, it is estimated that 10% of an organizations' employees are going to experience a significant bereavement (Foster & Woodthor-

pe, 2016), and in Portland public teaching service, bereavement leave accounted for about 1.2 days of absence annually, creating an overall impact over students (Portland Public Schools, 2012).

Grounded on the body of knowledge previously scrutinized in the above subsections, the following hypotheses can be raised:

(H1) Due to their higher fragility, older workers are likely to be absent for a longer period.

(H2) Vacations are a worker's right in most countries; yet, motivated workers that really enjoy their day-to-day activities are in less need of the break made available by vacations. In the opposite direction, but with similar results, workers that have not had vacations for a while are those that are key for the Public Administration service, and for whom there is not a replacement. This implies a higher probability of those PAE having their vacations interrupted by the need to get back to service. Thus, we postulate that workers going without vacations for a period are those for whom a future absence tends to be shorter than what was initially expected.

(H3) The literature corroborates common sense in that both occasional and prolonged sickness (Jean & Guédé, 2015) as well as disabilities are likely to increase the absence period. Therefore, we hypothesize that in PAE, (H3a), sickness leads to a longer absence, (H3b) as well as having disabilities.

Methods

Data Collection and Feature Selection

The experimental setup consisted in mono-database mining – data from different data sources aggregated to a centralized repository for the task of mining (Ramkumar, Hariharan & Selvamuthukumaran, 2013).

In January 2017, information from 17,600 PAE was collected from seven Portuguese public databases concerning employee absences that occurred in 2016. Specifically, two main sources of information were scrutinized: (1) absenteeism map, and (2) workers' details. The main goal was to predict the timespan of the next absence based on past information. Thus, such a goal is translated into a target feature (variable) that measures the absence of timespan (Nr.=17, name=AbsenceDays, in Table 1). The independent features (variables) are detailed in Table 1. The "origin" column defines if the feature was extracted or computed, while the "source type" categorizes the source of the feature into three types: user, absence, or entity information. Additionally, a "data type" column is exhibited to clarify the type of data according to the R statistical tool, which was used for the subsequent data analysis procedure explained later.

Feature selection and engineering is a key task in any data-driven model (Domingos, 2012). Moreover, real-world data tend to be incomplete, noisy, and inconsistent (Han, 2005), so the data has to be transformed and cleaned before it is loaded into a data warehouse in order that downstream data analysis is reliable and accurate (Risch *et al.*, 2009). As such, a thorough data preparation step was conducted to clean the dataset and select the most suitable features for the studied problem. Initially, the dataset was composed of 40 different attributes including the output variable, contemplating 59,163 observations (absences which occurred

in the Portuguese Public Administration during 2016), which represent the workers' absences, with different lengths and causes. After analyzing the outliers and incongruencies, the number of observations dropped to 36,499, as well as the selected features, which were 25, classified as "included" in the "status" column, following the procedure by Moro, Rita, and Coelho (2017).

Table 1

Features list

N	Feature Name	Origin	Source Type	Data Type	Description	Status
1	Entity	Extracted	Entity	Character	Worker's entity that is responsible for paying salaries and accounting for the absences	Included
2	WorkerNumb	Extracted	Entity	Character	The Number which identifies the worker	Excluded
3	Contract	Extracted	Entity	Character	Contract type between the worker and the institution.	Included
4	ContractSpecs	Extracted	Entity	Character	Contract's specifications	Included
5	Workplace_Location	Extracted	Entity	Character	Where the worker does their activities	Excluded
6	DayBegin	Extracted	Absence	Integer	First day of absence	Excluded
7	MonthBegin	Extracted	Absence	Integer	Absence start month	Excluded
8	YearBegin	Extracted	Absence	Integer	Absence star year	Excluded
9	DayEnd	Extracted	Absence	Integer	Last day of absence	Excluded
10	MonthEnd	Extracted	Absence	Integer	Absence end month	Excluded
11	YearEnd	Extracted	Absence	Integer	Absence end year	Excluded
12	DateBegin	Extracted	Absence	Date	Absence begin date	Excluded
13	DateEnd	Extracted	Absence	Date	Absence end date	Excluded
14	AbsenceCode	Extracted	Absence	Integer	Code which identifies the absence	Excluded
15	AbsenceDesc	Extracted	Absence	Character	Absence description	Included
16	CalendarDays	Extracted	Absence	Numerical	Absence calendar days (including weekends)	Excluded
17	AbsenceDays	Extracted	Absence	Numerical	Duration of the absence in working days	Included
18	AbsenceHours	Extracted	Absence	Numerical	Duration of the absence in working hours	Excluded
19	BirthDate	Extracted	User	Date	Worker's birthdate	Transformed
20	Gender	Extracted	User	Character	Worker's gender	Included

N	Feature Name	Origin	Source Type	Data Type	Description	Status
21	JobPosition	Extracted	Entity	Character	Worker's job position	Included
22	AcademicQual	Extracted	User	Character	Workers' academic qualifications	Included
23	LivingDistrict	Extracted	User	Character	Workers' living district	Included
24	PPAWorkDays	Extracted	User	Integer	Worker's days in PPA (antiquity)	Included
25	MaritalStatus	Extracted	User	Character	Worker's marital status	Included
26	ChildrenNumb	Extracted	User	Integer	Worker's number of children	Trans- formed
27	Nationality	Extracted	User	Character	Worker's nationality	Included
28	WorkHours_ Day	Extracted	Entity	Numerical	Worker's working hours per day	Included
29	WorkWeekdays	Extracted	Entity	Numerical	Worker's working days per week	Excluded
30	DisabilityPercent	Extracted	User	Integer	Worker's disability percentage	Excluded
31	Specificities	Extracted	User	Character	Worker's specificities	Included
32	DaysNo_ Absences	Computed	User	Integer	How many days with no absences?	Included
33	TimesAbsent_ LastYear	Computed	User	Numerical	How many times was the worker absent during the year?	Included
34	DaysAbsent_ SinceLast	Computed	User	Numerical	Sum of the worker's absences until the present absence	Included
35	Age	Computed	User	Numerical	Worker's age	Included
36	TimesAbsent_ SameMotive	Computed	User	Numerical	How many times was the worker absent for the same motive/ reason?	Included
37	HaveChildren	Computed	User	Character	Does the worker have kids?	Included
38	AbsentAfter_ Vacation	Computed	User	Character	Is the absence after vacation?	Included
39	DaysAfter_ Vacation	Computed	User	Integer	How many days was the worker absent after vacations?	Included
40	VacationDays	Computed	User	Numerical	How many vacation days did the worker have?	Included

Data analysis

One way of characterizing a database of customers is by computing their RFM characteristics (Moro, Cortez & Rita, 2015). These allow for capturing customer behavior in a very small number of features, as shown in Table 2. Still, the relative importance among RFM varies with the characteristics of the product and industry (Ibid.). Therefore, in this study, RFM is proposed for human resources. Table 2 shows how each of the three features was interpreted for absenteeism.

Table 2

Adapted RFM telemarketing features analyzed (Moro et al., 2015)

Factor	Citation	Application to telemarketing	Application to absenteeism
Recency	How recent is the last purchase? Time of most recent purchase The period since the last purchase The total days between the day of the latest purchase and analysis (days) The period since a customer last purchased	Months from the last purchase up to the current date	Days since the worker failed to show up to work? Was the motive the same?
Frequency	How often does the customer buy a product? Number of prior purchases Number of purchases made within a certain period Consuming frequency (times) The number of purchases made within a certain period	Number of times the client subscribed the deposit previously	How many times, in the last year, was the employee absent? How many days has the worker been absent since last time?
Monetary	The money spent during a certain period Amount of money in total consumed The amount of money that a customer spent during a certain period	The total amount of money the client subscribed in previous contacts	Total amount spent on temporary workers to fill in for the absent worker.

Using the 25 selected features as input to data mining modeling, a SVM was trained to model absence duration. This is a supervised learning technique that transforms the complex input space into a high m -dimensional feature space by using a nonlinear mapping that depends on a kernel (Silva *et al.*, 2018). A 10-fold cross-validation scheme was adopted for more robust validation of the model. In such a scheme, the dataset is split into 10 partitions, with the training set being composed of 9/10, while the test set includes 1/10. The partition selected for testing then rotates among all 10 partitions. The performance of the model was assessed using the mean absolute percentage error (MAPE) metric, which measures the percentage difference between the number of days of absence predicted by the model, and the real value. The results achieved are of a MAPE of 19.26%, meaning that the model can predict the duration of the next absence, up to 4 days, with an error lower than 5 hours.

These results enable us to proceed with the knowledge extraction stage. SVM is considered a black-box model. Thus, specific techniques are required for knowledge extraction. Specifically, the data-based sensitivity analysis assesses the model's sensitivity to varying each of the input features (Cortez & Embrechts, 2013). The result is a list of percentage relevance of each feature to model absenteeism. The six most relevant features, gathering about 59% of the importance, are linked, except for work hours per day, by the absenteeism profile of the worker, i.e., absence's motive and its recurrence. Thereafter, there was no visible pattern in the relevance features, as there is a mix of worker's characteristics, as well as, contract specifications and absenteeism records.

The discovery that the features related to the profile of the worker are less relevant than absence related features is quite interesting, mostly because it opens the door for a generic model that can be created without too much knowledge about the worker and, subsequently, this model can be generalized to all HR departments or all companies. This finding goes along with other studies' authors, previously mentioned in this article, who used past absences to predict future ones (Reis *et al.*, 2011; Roelen *et al.*, 2011; Laaksonen, He & Pitkaniemi, 2013).

Results and Discussion

Table 3 shows the major findings, relating the indicator (scenario of a feature) with the expected result in absence days (and working hours, using the average of 6 hours per day).

Table 3

Scenarios and expected absence days

Indicator	Expected (working hours = average 6 hours per day)
Absence with same motive	Up to 1 day (5.1 hours)
Bereavement leave and sickness	2 days of absence (12 hours)
Ambulatory care	Less than 1 day (4.6 hours)
High number of absence days (233 days)	1.3 days of absence (8 hours)
5 working hours per day	1.2 days of absence (7.2 hours)
No vacations for a long time (361 days)	About 1 day (6.5 hours)
Absent regularly (22 times)	About 1.2 days (7.2 hours)
30% disability	1.19 days of absence (7.1 hours)
Higher disability % (over 30%)	1.13 days of absence (6.8 hours)
No absences for a long period (140 days)	1.22 days of absence (7.3 hours)
Older worker (70 years old)	1.2 days of absence (7.2 hours)

By further taking advantage of the sensitivity analysis, it was possible to perceive how each of the most relevant features affected the number of consecutive days of absence and some conclusions were drawn.

Firstly, if it is the first time a PAE is absent for one of the motives, then it is expected that they will miss work for more than one day per year. However, if the worker keeps skipping work due to the same motive, the duration of the absence shall decrease, which goes against some studies that demonstrate that having suffered a previous sick leave episode implies a significant increase in the risk of experiencing a subsequent one (Roelen *et al.*, 2010; Reis *et al.*, 2011). Although, this might be explained by the feeling of motive recurrence and the suspicion about the veracity of the justification, which is a limitation that has been mentioned in previous studies (Beil-Hildebrand, 1996), or because the employee feels that be-

ing absent for a long time after missing work for the same motive might influence their “image” as a PAE (Mishali & Weiler, 2017).

Also, the motives bereavement leave and sickness tend to lead to a longer period of absence in Public Administration, followed by family assistance, which can get up to almost two consecutive days of absence. Sickness is also mentioned as one of the main reasons for public sector absenteeism (Jean & Guédé, 2015), where stress is highlighted as one of the main factors (George & Zakkariya, 2015). Bereavement leave and family assistance are tied to the family aspect (Spetch, Howland & Lowman, 2011). Among all the health problems, ambulatory care represents the shorter period of absence, with a duration between half a day to one full day of absence.

Effectively, the higher the number of days that the PAE missed work, the longer the duration of their next absence, which goes along with Roelen et al.'s (2011) study about prolonged sickness absence in the past and its impact on future absences. This corroborates H3a.

Likewise, PAE who work five hours per day will be absent for a longer period than others in the public sector, which, after analyzing the dataset, is associated with female assistants with ineffective service commission contracts. This conclusion is on the same page as Markussen et al.'s (2011) study up until the five-hour mark, after which this article shows the opposite – a decrease in the duration of absenteeism with the increase of working hours.

PAE who do not go on vacation for an extended period tend to be absent less than others in the public sector, confirming previous results (Westman & Etzion, 2001), and confirming H2. Taking a closer look at the dataset, it is possible to understand that mainly assistants and technicians, who are effective or in an equivalent regime, do not take vacations that often and so are the ones who should be absent for a shorter time. It is a rather controversial conclusion, as this discovery goes against some of the other studies' results about the role of vacations in absenteeism (Westman & Etzion, 2001), but it should not be discarded as the relationship between vacation and worker well-being is still unclear (De Bloom, Geurts & Kompier, 2012).

PAE who miss work up to 20 times tend to increase their absence duration, although after that it starts to stabilize. Furthermore, this finding is tied to the cumulative PAE absence days conclusion, since both contribute to longer periods of absence; results backed up by Roelen, et al. (2011).

Additionally, PAE with a 30% disability are the ones with a longer absence duration. Interestingly, the next absence duration of an over 60% disabled PAE is about 1.16 days (28 hours), which is shorter than the duration of a non-disabled worker's absence, as Kaye et al. (2011) exposed in their study on why employers do not hire and retain workers with disabilities. There are clear stereotypes surrounding people with disabilities about their poor performance and regular absenteeism, which, from the perspective of absenteeism, has been revealed to be inaccurate. Therefore, H3b is confirmed.

Moreover, PAE that are not absent for a period of 140 days (or close to 5 months) are more likely to be absent for a longer duration, confirming previous studies (Vlasveld *et al.*, 2012). Lastly, confirming H1, an older PAE tends to be

absent for a longer duration than a younger one, a finding aligned with the fact that age comes with a monotonous and significant rise in major disease absences (Markussen *et al.*, 2011).

Conclusions

The most concerning PAE profile is a 70 year old, 30% disabled, PAE with a schedule of five work hours per day, who has just come back from vacation, who mentions that they will miss work because they are feeling sick for the first time, but have already missed work many times for other reasons and for an extended period of time, over 140 days ago.

The RFM methodology had a significant role in the data analysis, managing to get all its computed variables in the 25th most important features, especially considering that five out of six of them were in the top ten most important features, concealing around 43% of the total relevance, which opens the door to using this methodology in other fields of study besides marketing.

To prevent absenteeism itself there are several studies with solutions or that have proven that a policy/reform had a positive impact on it, such as working from home, reduced workweeks and standard weekday work hours, all of which were helpful in reducing absenteeism (Kocakülâh *et al.*, 2016). Reducing the number of responsibilities given to a worker also reduces absenteeism (Gosselin, Lemyre & Corneil, 2013), and a reform on reducing sick leave compensation and increasing monitoring helped to diminishing the long duration hazards (De Paola, Scoppa & Pupo, 2014). Nevertheless, returning to work after an illness is dependent on medical and occupational factors, such as lack of job satisfaction, unsatisfactory relationships at work, or a physically demanding post (Pélissier, Fontana & Chauvin, 2014). On the other hand, public organizations should regulate their employees' vacations according to stressful periods as a way to reduce absenteeism (Westman & Etzion, 2001).

From an academia perspective, this study makes an important conceptual addition to the organizational behavior management area of investigation by providing insights concerning the factors that influence PAE absenteeism, through the development of a model to predict future absences in the Public Administration sector and revealing that the RFM method of data analysis can be applied in the HR area of investigation. Thus, our proposal expands on traditional human resources theories such as Public Service Motivation theory (Bozeman & Su, 2015), Person-Environment fit theory (Zacher, Feldman & Schulz, 2014), self-determination theory (Deci, Olafsen & Ryan, 2017), or Theory of Planned Behavior (Brouwer *et al.*, 2009). By borrowing the Recency, Frequency, Monetary model from the marketing literature, we show that RFM variables, which are known to have predictive value in the customer relationship theory, can also bring value to predicting absences, despite being a totally distinct domain. For managerial contribution, the PAE absence justifications can be used by HR departments to understand and comprehend how long their employees will be missing from work and act accordingly, including allocating other workers or subcontracting to fill the gaps left by those absences.

Limitations and Future Research

Even though the results of the article were quite impressive, there are some limitations that should be mentioned as an opportunity for future research. On one hand, the veracity of the absence motives could not be proven, so future research should implement a strategy to mitigate this limitation. On the other hand, the number of records of one absence day were disproportionate to the other records. So, it would be preferable to obtain a dataset with wider variety of absence records.

For future research, it would be interesting to add continuity to this article, i.e., add more years to the dataset in order to update the data and refine the model. Likewise, it would also be relevant to cross these findings with similar from other countries to understand the national differences in terms of absenteeism. Finally, it would also be interesting to cross absenteeism in the private sector with the results obtained in this article, so that it would be possible to know if there is a common model to be applied to both sectors or if each requires its own.

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