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Workforce Analytics in Teleworking

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ABSTRACT The recent COVID-19 pandemic has accelerated the interest in new software tools to monitor the computer-based activities of employees working remotely (teleworking), and the demand for better analytics functionalities to be offered, focusing on employees' performance and work-life balance. In this paper, we aim to analyze the habits of teleworking employees based on their interaction with the computer: how the employees are involved in different types of activities (actual work, recreation, documentation), and which are the most intensive periods. A conceptual framework for workforce analytics was developed for this purpose, together with tools and applications, that can provide useful information on different categories of activities where employees are involved. Knowledge generation is performed in four phases: collecting, processing, organizing, and analyzing the data to create valuable insights for the organization. Based on this framework, we developed a case study in an IT company, where two categories of employees, developers and software consultants, were monitored for 114 days, with 3.5 million events being generated and processed. The results showed different habits for consultants and developers, in terms of working activity structure, working schedule, inactivity time and interaction with the computer. Differences were also identified when we compared our results with previous research that monitored software developers working in-house: remote workers tend to organize their program for a longer period during the workday, and spend less time on meetings but longer time for programming. On the other hand, both categories of employees (in-house and teleworkers) show highly fragmented work, switching windows after very short periods of activity, with a potential negative impact on productivity, progress on tasks, and quality of output. The research results can be used in future employee productivity studies when searching answers to a fundamental question for workforce analytics – why are some employees more productive than others?

INDEX TERMS Computerized monitoring, workforce analytics, employee performance, data processing, data engineering, data analytics.

I. INTRODUCTION

The technology-driven change associated with the fourth industrial revolution that we are currently witnessing, has profoundly changed all aspects of human life–the way people interact, learn, work, and their expectations in general. Unlike the second industrial revolution, which in the 19th century brought people from rural areas into cities to work in factories, an increasing number of people can work our days remotely [1]. This paradigm shift was brought about by the wide availability of reliable and cost-effective hardware and software solutions developed in the field of IT. Today, most households have computers and different devices connected to internet, and this situation allows access to a myriad of digital platforms and cloud services, which in turn facilitates remote working [2].

The concept of teleworking [3], which means that an employee performs work from a remote location (i.e., not in an office provided by the employer) using a computer, was intoduced by Nilles *et al.*[4] and Kraemer [5], and can also be found in the literature as remote working or telecommuting. Since then, teleworking has evolved over three generations: home office, mobile office, and virtual office [6]. In the last generation of telework, the information is stored in clouds

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and networks, and the employees only need small devices to conduct their daily working tasks.

Over the years, many companies have investigated and experimented with this concept, in the hope of increasing their profitability and performance indicators [7]–[10]. These studies have found that moderate levels of remote working can indeed be beneficial for both the employees (who benefited from the flexibility associated with remote working) and employers, by reducing expenses associated with physical offices [11], while excessive levels will likely harm both the well-being and productivity of employees. Consequently, the consensus is that remote working, involving employees working a few days per week remotely, will become increasingly common in the future [12].

A recent report [3] identified the jobs that can be performed from home, and defined *teleworkability* as *the technical possibility of providing input remotely into a given economic process.* Nearly all financial-services employment is *teleworkable* (93%) as well as nearly four in five employees in information/communication (79%), and around two-thirds of employees in real estate, professional, scientific and technical activities, education and public administration [3].

The circumstances of the Covid-19 pandemic, have suddenly and unexpectedly forced companies worldwide to resort to remote work. On the one hand, this has proven the usefulness and effectiveness of the employed digital technologies. On the other hand, it has outlined the imperative need to investigate and evaluate the effects of remote working from a significantly broader perspective that considers the social, political, legislative, and economic aspects associated with remote working. Another report *Teleworking during the COVID-19 pandemic and beyond* [13] concluded that, in the future, both private companies and public organizations should consider conducting an important part of their activity in remote environments, recommending continuous monitoring of employees' activity and the necessity to evaluate employees' performance and satisfaction in this new virtual work environment.

Such evaluations encounter many difficulties, due to data accuracy, confidentiality, and security issues [9]. Data processing and analysis are other issues, especially when discussing about large amounts of data and the diversity of variables involved in the analysis.

Starting from these challenges, the aim of this paper is to analyze the habits of the teleworking employees, based on their interaction with the computer: how the employees are involved in different types of activities (actual work, recreation, documentation), which are the most intensive periods during a workday. The results were also compared with similar research performed in a traditional in-house environment.

A conceptual framework for workforce analytics was developed for this purpose, together with tools and applications, that can provide useful information on different categories of activities in which employees are involved, and on the process performance. The framework is flexible, can integrate different tools and applications to serve different purposes and evaluations based on company-specific objectives, can be applied in both teleworking and in-house scenarios, and can be useful for individual development–as a self-monitoring tool used to increase productivity and self-reflection, and for HR (Human Resources) managers and consultants, when analyzing employees' activities. It can also process large amounts of data that will result while monitoring a large number of employees for longer periods.

Based on this framework, we developed a case-study in an IT company, were approximately 3.5 million events generated by five employees working remotely for 114 days, were collected, using a keystroke logging program. The "clean" data, which resulted after removing inconsistencies, was imported in SQL and NoSQL databases using data connectors developed by our team in previous projects. Using clustering techniques, and a software application based on a real-time ranking query, the resulting keywords were assigned to specific working activity categories which were further processed using data analysis and visualization tools. The resulted regression analysis and the histograms answer the question we started from: how a workday looks like and which are the habits of the employees.

The paper is organized into four sections, starting with Section 2, briefly reviewing the state-of-the-art. Section 3 describes the proposed approach, introduces the framework for workforce analytics, and presents the results after using the framework in a teleworking scenario. Finally, Section 4 presents the limitations of this study, and Section 5 highlights the paper's conclusions, and suggests future research directions.

II. LITERATURE, RESEARCH PROBLEM AND QUESTIONS

A. WORKFORCE ANALYTICS IN TRADITIONAL AND REMOTE SCENARIOS

Human resource departments raise a number of difficulties in the assessment of employees, due to factors such as radical changes in the labor market, the emergence of new skills and the disappearance of others considered traditional, diversification of skills and increasing requirements for analytical solutions for solving different problems, teamwork, communication [14], data analysis and interpretation, and objective correlation with performance indicators [15], [16]. In addition, employees' assessments are tense, stressful, and induce anxiety [17].

Workforce, or human resources/people analytics [18], started as a small administrative endeavor and have gradually evolved to provide advanced diagnostic and predictive capabilities that are able to enhance employee engagement and retention. Statistical models and other techniques are used to analyze worker-related data, allowing leaders to improve the effectiveness of people-related decision-making and human resources strategy [19], generating benefits for organizations through digitally powered analytics solutions.

Huselid [20] defined workforce analytics as *processes involved in understanding, quantifying, managing, and improving the role of talent in the execution of strategy and* *the creation of value, including not only a focus on metrics (e.g., what do we need to measure about our workforce?), but also analytics (e.g., how do we manage and improve the metrics we deem to be critical for business success?)*

Numerous factors are currently interacting to raise the importance of workforce analytics for human resources (HR) professionals, with two standing out from the rest [21]: a combination of internal and external factors, regulatory requirements, and labor market factors that are changing faster than it is possible to monitor using intuition and observation alone, and the new analytic possibilities opened up to HR by rapid developments in technology for managing and analyzing big data. There is a consensus that workforce analytics presents a world of opportunities to improve business effectiveness, which we have only begun to explore [21].

In a survey conducted in 2019, in 21,869 organizations from the EU 28, 51% of organizations reported the use of data analytics. Out of these, 24% declared that they use such tools for process improvement, 5% reported their use for monitoring of the employees, and 22% reported for both purposes, with the conclusion that data analytics tended to be used with the objective of improving processes, more than for employee monitoring [9].

Various studies [2], [6], [13], [22]–[24] have highlighted, on the other hand, significant challenges: employees work more hours than in the physical environment and changes in work routine appear, making it increasingly difficult to separate professional activities from personal life because an important part of working tasks is performed in the evenings and on weekends. All these factors make it more difficult to record, monitor, and control the working schedule [9].

B. PERFORMANCE EVALUATION AND WORKING HABITS; THE CASE OF DEVELOPERS

New challenges arise when assessing the performance of employees in the remote working environment, in terms of data collection, accuracy, confidentiality, and security of collected data [11].

Solutions to these challenges could be provided by the automatic data collection tools, such as employee monitoring, legalized by specific laws in several countries (for instance, some European countries have regulations on the registration of working time of tele-employees [9]). In this case, the challenges arise from the difficulties in data collection, processing, and analysis, as well as the management of the enormous volume of data generated.

If traditional monitoring of employees was initially performed by an observer or supervisor, the last generation monitoring systems can observe, record, and analyze voluminous data about multiple dimensions of employees' performance [25], [26] behavior, and/or personal characteristics [27], giving a better view of employee performance and alignment with organizational performance.

Peeters *et al.* [28] proposed a framework, called *The People Analytics Effectiveness Wheel,* with four categories of ingredients that a people analytics team requires to be effective: enabling resources, products, stakeholder management, and governance structure, which can serve as an initial point of departure for enhancing decision-making and contributing with people analytics to organizational performance. Falletta and Combs [29] introduced *the HR analytics cycle* as a proactive and systematic process for ethically gathering, analyzing, communicating and using evidence-based HR research and analytical insights to help organizations achieve their strategic objectives.

There are also plenty of studies in software development companies, showing how developers spend their working time, and which are the factors affecting their productivity.

In a long observational study (1000 h), Astromskis *et al.* [30] reported the results conducted in an industrial environment, in which they captured interaction of the six developers with various applications available in their workstations. They found that developers spend most of their time (approx. 61%) in development activities while the usage of online help is limited (approx. 2%).

Minelli *et al.* [31] present an in-depth analysis of how developers spend their time, based on an IDE (Integrated development environment) interaction dataset consisting of ca. 740 development sessions by 18 developers, amounting to 200 hours of development time and 5 millions of IDE events. They found that, on average, developers spend 70% of their time performing program comprehension and 14% on rearranging the using interface of the IDE, that is, resizing or dragging windows. The time spent for editing and navigating source code is respectively 5% and 4%. The large part of development is occupied by mental processes (*i.e.,* understanding) and, in the remaining time, a developer has to deal with inefficient user interfaces to read, write, and browse source code.

Many other studies, presented in Meyer *et al.*, are indicating a very wide variety of the *time working on main coding tasks*, ranking from 9% to 61%, and also of other activities that fragment developers' workdays [32].

There is also significant literature that focuses on defining and analyzing productivity in different industries. Meyer et. al. [33] reviewed the relevant literature for software development companies and indicated a commonly accepted list of key performance indicators (KPIs): number of modification requests and added lines of code per year, number of tasks per month, number of function points per month, number of source lines of code per hour, number of lines of code per person month of coding effort, amount of work completed per reported hour of effort for each technology, the ratio of produced logical code lines and spent effort, the average number of logical source statement output per month over the product development cycle, and time (in days), to resolve a particular modification request. It is also accepted that such KPIs capture only a small part of a developer's work, which makes it difficult to provide a more holistic picture of a developer's work and productivity [34].

The recent COVID-19 pandemic has accelerated the interest in new software tools to monitor the computer-based activities of employees working remotely, and the demand for better analytics functionalities to be offered, focusing on employees' performance and work-life balance [22].

C. AIM AND RESEARCH QUESTIONS

Previous studies, mostly performed for employees, working in-house (especially IT specialists), are indicating that the impact of different factors on productivity and well-being of the employees varies a lot, suggesting that the opportunities for productive behavior changes might differ amongst individuals [32].

Our study focuses on employees working remotely, and aim to see how the working life of the employees looks like, by answering the following questions:

RQ1. How are the professional activities distributed during a workday?

RQ2. Which are the most intensive periods for a workday and when are the highest idle times recorded?

RQ3. Does a traditional in-house workday look different when compared with a remote one?

In our study we will focus both on developers and software consultants, trying to identify common point and differences in working behavior.

III. CONCEPTUAL FRAMEWORK FOR WORKFORCE ANALYTICS

To answer the RQs, we developed a conceptual framework for workforce analytics (Figure 1), which comes with a structured approach, and can integrate different tools and applications, to monitor the employee's activity, and serve different purposes and evaluations based on company-specific objectives. Knowledge generation is performed in four phases: collecting, processing, organizing, and analyzing the data to create valuable insights for the organization. The framework can process large amounts of data that will result after monitoring a higher number of employees for longer periods.

We decided to use two types of data processing approaches, and the results were compared to each other for integrity and accuracy purposes:

- In the first approach, data are uploaded to a non-relational database that is accessed through AQL queries, by a dedicated platform for data processing, named *SW Workforce Analytics Platform*, developed in a previous project by our team [14], which is able to extract relevant metrics for evaluating employee performance.
- In the second approach, an application was developed in Java to organize, store, and process the information contained in raw files, the recorded data being uploaded and saved in a traditional SQL database.

A. METHOD

We chose a medium-sized company that develops and implements financial and business solutions software with 25 experienced employees of different ages located in three Romanian cities. Half of the employees hold programming positions, and the rest are software consultants, accountants, and human resource managers. Since spring 2020, due to the circumstances of the Covid-19 pandemic, the company has transferred its activities to the remote environment.

TABLE 1. Data for the study.

Id	Recorded files / days	No. of processed files	No. of recorded events	Age	Gender	Experience (years) in company	Position in the company
C1	21	16	427835	36	M	15	Software consultant
C2	7	4	71852	41	M	2	Software consultant
P1	51	46	1734216	38	M	15	Developer
P2	19	14	234784	38	M	16	Developer
P3	34	34	1022843	43	F	13	Developer

The participants included in the study consisted of five employees: three senior software developers and two senior software consultants. The employers were selected based on their willingness to take part in the study and also on the level of interaction with the computer: while the IT specialists can perform most (or all) of their activity from the computer, the consultants need to interact with customers, and could have a different work routine.

All selected employees had more than 10 years of experience (employee C2 received this experience in the analyzed company and in other companies). More sample data are provided in Table 1.

The employees agreed to install a key logging application – InputLog, and to activate it at the beginning and the end of the workday. Data collection and analysis procedures together with the validation criteria were established, all these are described in the subsequent section B-D.

Data were collected for approximately 3 months, between October and December 2020, over a total of 130 workdays. A number of 16 files were excluded from the study (from a total of 130 files) because they contained inconsistencies and error messages.

There is no uniform distribution of the number of days per employee, as some employees worked for a smaller number of days, for various reasons, including medical ones.

We excluded implementers, marketers, and administrators in the sample, as they do not perform remote activities, most of the working time being carried out at the client's location or in the office.

The participants were trained and provided with all technical details on how to use the data monitoring application, and were given access to the location where the data were saved to have control over their records. Ethical issues were also discussed and agreed upon, and the employees were assured of the anonymity and confidentiality of their data.

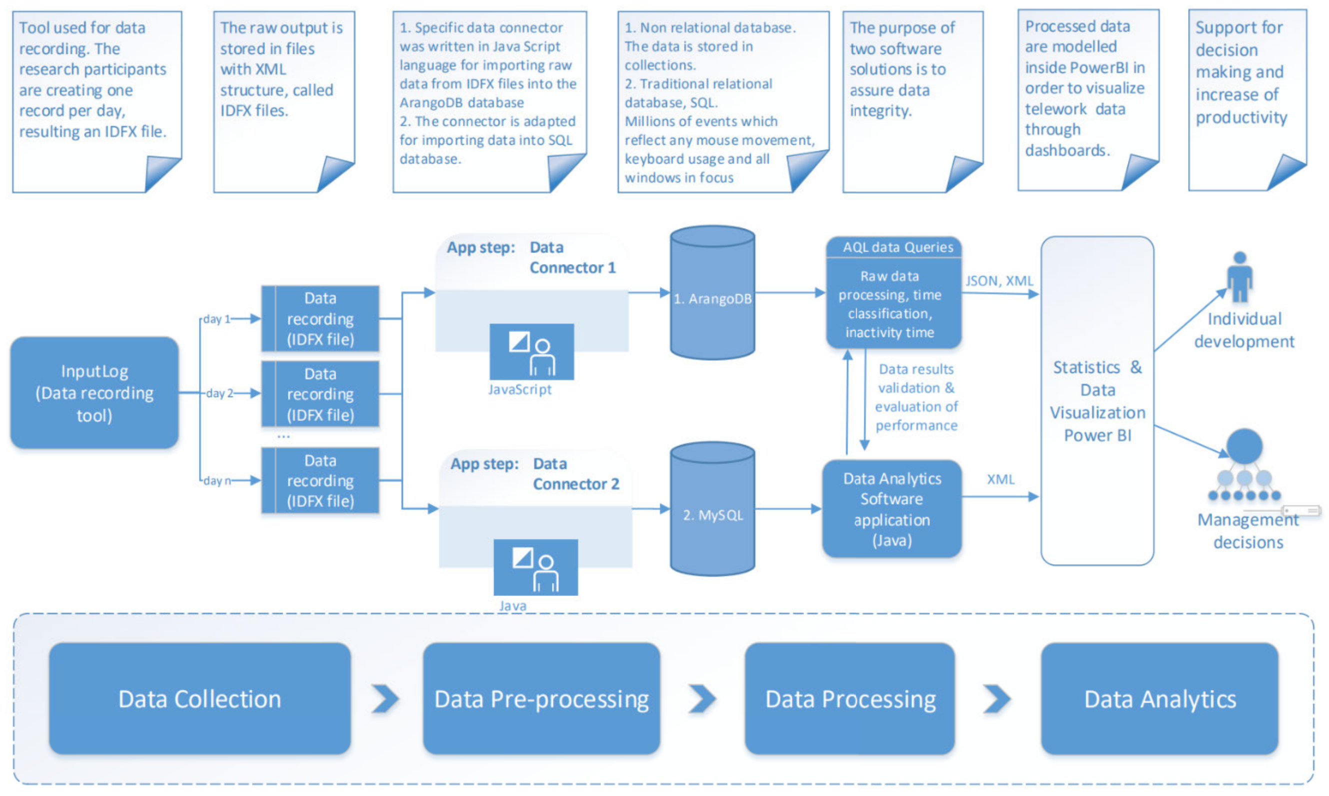


FIGURE 1. Conceptual framework for workforce analytics.

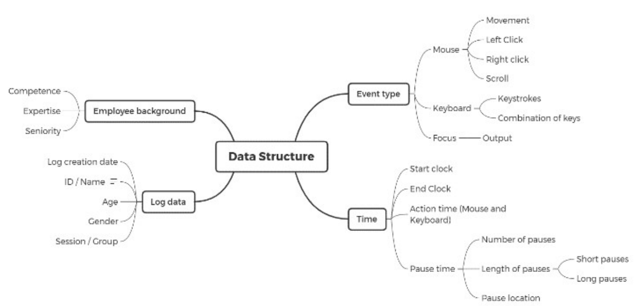


FIGURE 2. Data structure.

B. DATA COLLECTING

An important challenge in workforce analytics is to collect the data to be used later in the analytics stage; besides accuracy and security, it is also important to assure privacy and protection rights.

The raw data (non-structured data) is generated by the employee during interaction with the computer peripheral devices: keyboard (number of keys per minute, key combinations), mouse (number of clicks per minute, movement), focus (type of focus windows, number of context switches), and timestamp (the exact time and date for each of the previously presented events), and can be structured as presented in figure 2.

These raw data can be collected by creating dedicated software solutions that record using API interfaces, or by using recording tools, such as InputLog, ScriptLog, and uLog [35].

We decided not to use applications that already provide data processing and visualization solutions, and choose applications that allow data to be recorded and provided in a raw format. After analyzing keyloggers solutions, such as ScriptLog, InputLog, and uLog, we finally chose InputLog, which can provide data in an unprocessed manner, and it can record mouse and keyboard data together with window titles.

C. DATA PRE-PROCESSING

To ensure that the data collected can be automatically loaded into databases and further explored and processed, the following activities were performed:

- *Filtering*. Data are retrieved from multiple sources, and human errors or errors generated by collection tools and the collection process may occur. Through visual inspection and automatic scripts, inconsistencies and missing and duplicate values (for example, multiple records from the same person over the same period of time) have been identified and removed.
- *Anonymization*, by encrypting/removing personal information, thus ensuring all confidentiality requirements.
- *Aggregation* around the constants: employee and time. Thus, all data were processed according to the employees and their role in the organization and depending on when the events occurred (daily analysis was performed throughout the research period).

- *Automatic import*. The IDFX-collected files (figure 1) have an XML structure that contains a root and all events as nodes of type <event>. These nodes have a classic xml structure with the properties described by start time, end time, title subnodes, and also by the attributes of the nodes, *focus* or *mouse*. These raw data need to be transformed into a data set that contains only numerical or categorical data, and, for better accuracy purposes, we decided to use two types of databases, for the automatic import of the collected files: ArangoDB (NoSQL) and MySQL. For each solution, we wrote a Data connector.

Data connector 1 uses a platform developed by our team in a previous project, *SW Workforce Analytics Platform* [14].

To ensure an appropriate structure and facilitate access to the data, session and meta-information were added to each event, and the attributes were translated into a JSON object. We also need to introduce sorting based on timestamps, as the events generated by the Inputlog are not chronologically stored.

The calculations were performed in the first attempt dynamically, in queries (calculation of time interval, sorting of events), but we found that processing a large volume of events is time-consuming and decided to move them back to the preprocessing stage. To optimize the process, two periods of time were calculated to be saved directly in the database:

- *deltaT* - period of event (mouse, keyboard or focus event types):

$$\begin{aligned} delta\ T\ &= next\ Event\ Start\ Time \\ &\quad - Current\ Event\ Start\ Time \end{aligned} \tag{1}$$

- *deltaTfocus* - period of focus event (active time on each window):

$$\begin{aligned} delta\ T\ focus\ &= next\ Focus\ Event\ Start\ Time \\ &\quad -current\ Focus\ Event\ Start\ Time \end{aligned} \tag{2}$$

One condition to be fulfilled here is:

$$SessionTime = \sum_{i=0}^{n} deltaTfocus, \tag{3}$$

where n represent number of focus events in one session.

SessionTime represents the total recorded time in a day, and is calculated as the difference between the last and first focus event.

Data connector 2 is an application developed in Java- the recorded data being uploaded and saved in a traditional SQL database. The keywords associated with each type of activity (work, documentation, and recreation) were also saved in the database.

The results generated using these tools were compared to each other for integrity and correctness evaluation purposes.

D. DATA PROCESSING

In order to answer the RQ1: *How are the professional activities distributed during a workday*? we introduced the following types of activities:

Total (work) time, represents the time elapsed from the first interaction with computer until the last one, during a workday:

$$TotalTime = \sum_{i=1}^{n} \frac{ActiveTime_i + Inactivity_{Long\,Breaks_i}}{n} \tag{4}$$

$$ActiveTime = \sum_{i=1}^{n} \frac{ActiveTime_i}{n} \tag{5}$$

$$ActiveTime_i = \sum_{j=1}^{4} ActivityType_j, \tag{6}$$

where:

- n – number of recorded days
- i – index of a day
- ActivityType $\in$ {*ActualWork*, *Documentation*, *Recreation*, *Other Activities*}
- j – index of ActivityType

ActiveType, comprises the activities directly associated to the specific jobs:

- *actual work*. This category includes all programs/ applications used to carry out activities specific to the employee's job prescription: programming (Eclipse, Java, Notepad ++), remote communication (Outlook, Skype, WhatsApp, Zoom, Windows Live Mail), accounting (conta.ini), and tools specific to the company's field of activity (Sqlyog, AnyDesk, Putty).
- *documentation*. This category includes applications used as preparation to carry out work-specific activities: Microsoft Office, Acrobat Reader, and various files in pdf format. In this category, search engines related to employees' jobs were also introduced, while filtering searches specific to recreation periods.
- *recreation and informal learning*. In this category were classified those searches that targeted sites specific to socialization (Facebook, personal e-mail address), online shopping, informal learning (YouTube), news websites, and gaming (FlashScore, locomotive, Pinterest, and train).
- *other activities*. This category includes activities that are not repetitive and cannot be included in a specific category. It has been established that this category to be limited to 10% of the total time spent.

Based on the previous research performed by Meyer *et al.* [34], we defined *Inactivity* as long and short breaks:

Long break: at least 15 minutes with no interaction with the computer [34].

Short break: period between 2 and 15 min with no interaction with the computer

Assignation of the keywords, generated by focus-type events (active windows and applications), and mouse and keyboard events, to the relevant category, was performed in two stages: first, we identified the keywords, and second, we assigned the keywords to the relevant category.

For keyword identification, we generated a map using mapVOSviewer, a tool that uses advanced layout and clustering techniques, showing relationships between keywords (characterizing the title of activity/application at which the employees are focused), as well as how often each item occurred within the network and how often the elements appear. The use of the program also facilitated a combination of the analyzed set of data into clusters.

To assign the keywords to activity categories, we developed a software application based on a real-time ranking query. Information extraction is based on user work sessions imported into the database, and is implemented using ArangoDB functions, to create groups and execute aggregation functions.

The work sessions are determined based on the timestamp of the imported events, and two collections are created in memory, one that filters all events/participant/session and one for focus/participant/session events. For each resulting category, the *SessionTime* is calculated.

Since the title of a window can contain keywords from all three categories, we established the following priority criteria for the activities: actual work/recreation/documentation.

For each focus event, a time window consisting of [*start-time and endtime*] was created to determine what events occurred while a window was displayed on the screen. Thus, we can identify downtime (associated with breaks) when no activity occurs in the current time window.

The results were also reviewed by the organization, and inconsistencies were removed, the table from Annex 1 being generated, where keywords were assigned to one activity category.

Based on the duration of the focus type events, and keyboard and mouse events, the application provides information related to the professional day, divided by types of activities and time intervals (when the employees start/finish working, the most intensive periods), and is also able to identify, and extract the inactive times (long and short breaks) from the active times.

In addition to structuring the workday by type of activity, the application allows, also by assigning keywords (Figure 3), to see how the employees are using different applications, and where they spend more time. Another functionality of the application is the dynamic allocation of keywords by an administrator or even the user, in order to adapt the application to other needs, such as participants from other job positions or even from other companies. Thus, the operator can add other keywords from the recorded events, until the desired degree of identification is reached. All these keywords will be stored in the database and used for further processing, as the application "learns" to allocate focus events to those predefined types of activities.

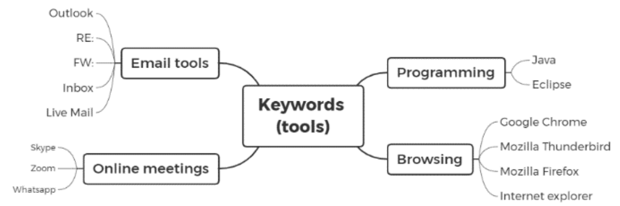


FIGURE 3. Assigning keywords to applications types.

TABLE 2. Average time for different activities (hours/day).

	Meeting (hours)	Email (hours)	Programming tools (hours)	Web Browsing (hours)
All participants	0.36	1.00	2.60	2.42
Programmers	0.41	1.01	3.12	2.46
Consultants	0.13	0.91	0.18	2.22

All information resulting from the processing is returned to JSON objects that we further imported into PowerBI and Minitab, for future exploration and analytics.

E. DATA ANALYTICS

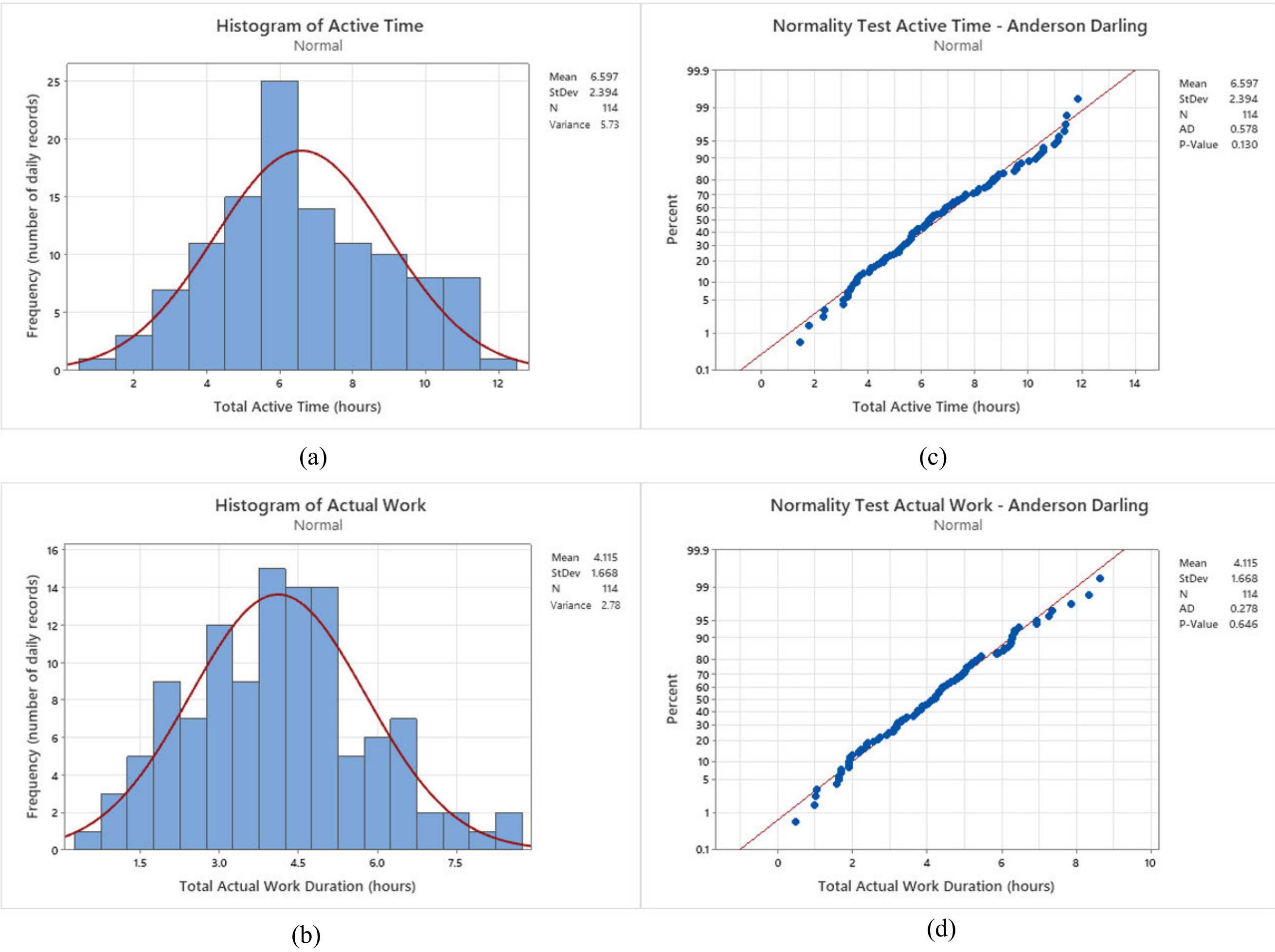
In this stage, Minitab was used for histograms and regression analysis to estimate the relationship between different variables.

The employees were observed for 114 days. In this period, they were connected, on average, 9.60 hours/workday, with an active time (after excluding long breaks) of 6.59 hours/day (Figure 4a), distributed as follows:

- an average of 4.11 hours (62.4% of the time) were spent on performing job-related tasks (actual work) (Figure 4b), including programming (for programmers) or accounting applications (for consultants);
- approx. 1.50 hour (22.9% of the time) was used for documentation, that is, the employees were browsing on Microsoft Office applications or on web search engines;
- approx. 21 minutes (0.35 hours, 5.3% of the time) were spent on recreation or relaxation activities, the most common applications/programs used: socializing and communication, search engines (which, in this case, are used to search for topics of personal interest), news or shopping sites, etc.;
- for approx. 43 min (0.72 hours, 9.4% of the time) on average, the employees performed various activities that cannot be classified in any of the previous categories.

Moreover, there is a standard deviation of 2.39 hours from the average, when we analyzed the Total active time, respectively a 1.67 hours standard deviation from the average for the Total actual work (figure 4c and 4d).

The tools and applications used more frequently were those related to programming or writing code (on average 2.60 hours/day), followed by browsing the web pages (on average 2.42 hours/day), e-mail (average 1 hour/day), and online staff meetings (average 21 minutes per day) (Table 2).



Variable	N	Mean	StDev	Variance	95% CI for σ using Bonett	95% CI for σ using Chi-Square
Total Activ Time (hours)	114	6.59	2.39	5.73	(2.15, 2.71)	(2.12, 2.75)
Total Actual Work (hours)	114	4.11	1.67	2.78	(1.48, 1.91)	(1.48, 1.92)

where σ: standard deviation of variables (Total Active Time, Total Actual Work)

FIGURE 4. Total active time and actual work time.

There are (as expected) significant differences for programming time when comparing programmers (3.12 hours/day) and consultants (0.18 hours/day), while for email and browsing activities the time spent is approximately the same for both categories.

Programmers spent about 0.41 hours/day in videoconferences, while the consultants spent 0.13 hours, which drives us to conclude that consultants prefer phone or direct meetings to communicate with customers. This affirmation is supported by another finding: the average working time (as interaction with computer) is 5 h/day for software consultants and 7 h/day for programmers.

Significant differences can also be observed in terms of:

- *context switch duration* (time spent in one activity between switching to another one): mean 17.65 seconds, stdev: 7.551 (for programmers), mean: 30.76 seconds, stdev: 20.95) (for consultants), Figure 5;
- *average number of focus (active windows and applications) events/day*: 2223 (programmers), and 1195 (consultants) Table 3.

The obvious conclusion is that programmers have a more dynamic interaction with computers, opening almost a double number of windows and spending half time in each one when compared with consultants.

RQ2. Which are the most intensive periods for a workday and when are the highest idle times recorded?

By dividing the workday in two-hours intervals (Table 3), we found that the most intensive working period for programmers was between 10.00 and 16.00, with an active time between 51 and 57 minutes at each two-hour interval; for consultants, instead, we have a peak of approximately

TABLE 3. Time spent with specific activities.

		Time interval							
		<8:00	8:00-10:00	10:00-12:00	12:00-14:00	14:00-16:00	16:00-18:00	>18:00	Total
Actual work **Programmers**	min(average/employee)	0	19.27	56.13	51.39	57.61	37.87	40.35	262.6
	%	0.02%	7.34%	21.37%	19.56%	21.93%	14.42%	15.36%	
Actual work **Software Consultants**	min(average/employee)	0	23.8	42.66	37.04	30.76	35.1	5.22	174.6
	%	0.00%	13.63%	24.43%	21.22%	17.62%	20.11%	2.99%	
Documentation **Programmers**	min(average/employee)	0	7.07	19.95	18.23	15.68	10.5	21.09	92.52
	%	0.02%	7.64%	21.56%	19.70%	16.95%	11.34%	22.79%	
Documentation **Software Consultants**	min(average/employee)	0	10.68	20.49	16.87	16.18	12.68	5.25	82.15
	%	0.01%	13.00%	24.94%	20.54%	19.70%	15.43%	6.38%	
Recreation **Programmers**	min(average/employee)	0	1.53	3.43	3.92	3.3	2.73	9.15	24.06
	%	0.00%	6.40%	14.30%	16.30%	13.70%	11.30%	38.00%	
Recreation **Software Consultants**	min(average/employee)	0	1.79	1.2	1.46	1.78	0.81	0.08	7.12
	%	0.00%	25.15%	16.87%	20.50%	24.97%	11.42%	1.09%	
Inactivity **Programmers**	min(average/employee)	0	4.78	22.16	35.42	35.60	42.57	42.96	183
	%	0.00%	2.61%	12.08%	19.30%	19.40%	23.20%	23.41%	
Inactivity **Software Consultants**	min(average/employee)	0	12.41	35.85	49.37	46.97	25.54	9.11	179.25
	%	0.00%	6.92%	20.00%	27.54%	26.21%	14.25%	5.08%	
Number of focus events **Programmers**	average/employee	1.06	156.16	457.9	457.49	477.01	333.45	339.81	2223
Number of focus events **Software Consultants**	average/employee	0	145.45	320.5	267.15	232.25	197.6	32.1	1195
Number of mouse events **Programmers**	average/employee	4	1031	3396	3744	3864	2843	2960	17842
Number of mouse events **Software Consultants**	average/employee	0	1694	4011	3186	2944	2480	921	15236
Number of keyboard events **Programmers**	average/employee	4	1012	2999	3111	3058	1905	2550	14639
Number of keyboard events **Software Consultants**	average/employee	0	1144	2395	2054	2080	1289	412	9374

42 minutes within the 10.00-12.00 interval, and lower periods during the 12.00-16.00 intervals, followed by another peak. In our interpretation, consultants are solving their office-specific tasks between 10.00-12.00, discussing with customers during the next period (12.00-16.00), while returning later in front of the computer to process the outputs.

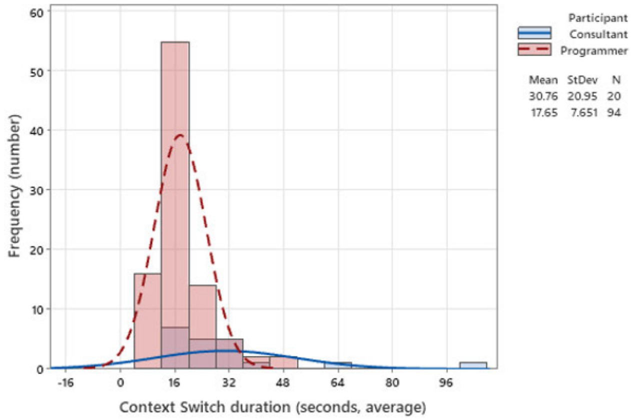


FIGURE 5. Context switch duration: consultants/programmers.

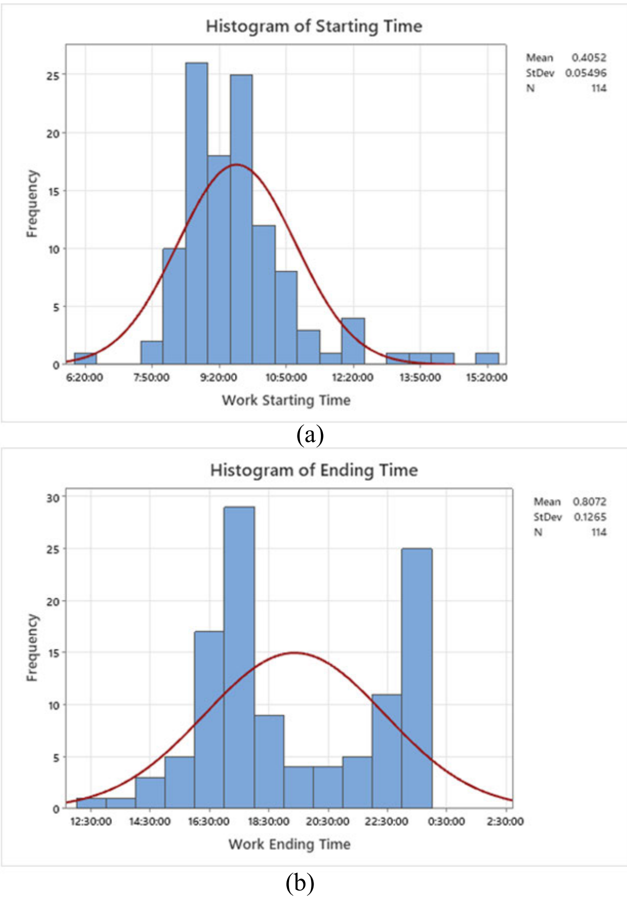


FIGURE 6. Start/Ending Times for the workday.

The histogram in figure 6 provides a better image of the employees' habits:

- The working activity usually started between 08:00-10:00 (the peak on the histogram from figure 6a), with very few cases when the work started earlier (6.20 the earliest).
- The earliest time when employees finished their work was 12.30 (again, in very few cases), and the latest was 23:59 (fig. 6b). There are two peaks in this graph, indicating that the employees usually finish their work between 16:00 and 18:00 and late in the evening, after 20.00.

TABLE 4. Number of short/long breaks.

Break type	Number of breaks	Breaks / day	Breaks / recorded hour	Breaks / active hour
Short breaks (2-15 min)	1602	14.05	1.50	2.21
Long breaks (longer than 15 minutes)	444	3.89	0.41	0.61

The conclusion from this figure is that most of the workdays are within the ''normal'' schedule, between 9.00 – 17.00, with the exceptions indicated above, when employees are moving some duties later in the evening, preferring to take some personal activities in the middle of the day.

Inactive time

The employees are taking an average of 3.89 long breaks (inactivity longer than 15 minutes) per day (or 0.41 breaks/hour), which we assume were used for lunch, or for other personal activities (Table 4).

At the same time, there are on average 14.05 short breaks (inactivity between 2 and 15 min) per day (or 1.50 breaks/hour), which we assume are spent with program comprehension, coffee breaks, or some other personal activities, as shown in [34].

It is noticed (Table 3) that the periods of inactivity increased, and even exceeded the actual work, as the programmers and consultants approached the end of the workday, which is attributed to the increase in the fatigue level.

RQ3. Does a traditional in-house workday look different when compared with a remote one?

We compared our results with those obtained by Meyer *et al.* [34], who used a monitoring application logging the currently active process and the events for a mouse click, movement, scrolling, keystroke, window title, at 20 professional software developers from four companies to investigate how they spend their workdays and what activities they perform while working in-house.

The comparison was possible due to the analyzed indicators, part of which were similar in both pieces of research (Table 5). On the other hand, there were significant differences in the structure of the workday (eg. in [34], the evaluations are made related to the types of applications used, and in our research, we structured the workday on the four categories of activities (see Chapter III).

The total workday time (time elapsed between the first and last computer interaction) was longer for the employees working remotely (9.39 h) compared with those working in-house (8.4 h), while the number of long breaks/days is about

TABLE 5. In-house vs remote workday.

Meyer's (2017) Data [34]	Our Data
20 employees, 4 software companies / 200 days	5 employees/ **3 programmers** 1 software company / 114 days
Meyer's (2017) findings (in-house) [34]	*Our findings – teleworking (only for programmers)*
Average recording time: 8.4 hours / day	Average recording time: 9.39 hours / day
The number of long breaks in which developers did not interact with their computer for longer than 15 minutes averaged 3.3 per day with a total length of 54.7 minutes	Total length of long breaks: 183 minutes (3 hours and 3 minutes)
Developers spend a fourth of the total working time (approx. 2.1 hours) on coding related activities	3.12 hours / day used on programming
Approx. 10% of the total working time (0.84 hours) is spent with planned and informal meetings	0.41 hour / day is spent in meetings
Approx. 14.5% of the total working time (1.21 hours) is spent on emails	1.01 hours / day is spent on emails
Developer's work is highly fragmenting, spending very short amounts of time (0.3 to 2 minutes) in one activity between switching to another one	Mean of the context switch duration (time spent in one activity between switching to another one): is 17.65 seconds, with stdev: 7.551

the same: 3.89 vs 3.3; however, the total length of these breaks cumulated is much longer for remote workers (3 hours and 3 minutes, vs 54 minutes). In our interpretation, this indicates that remote workers tend to spread their activity for a longer period of time, preferring to perform some other activities, during the "normal" program. 3.12 hours/day are spent with programming tasks by the remote employees, with approx. one hour more compared with the in-house colleagues; one explanation could come from the time "saved" with meetings (here, remote employees spend approx. half time compared with in-house employees), and with other activities (including collaborative activities, communication with colleagues, etc.) taking place in the physical office.

Both categories of employees show highly fragmented work, switching windows after very short periods of activity, with a potential negative impact on productivity, progress on tasks, and quality of output [34].

IV. LIMITATIONS AND VALIDITY

The employees involved in this study are IT specialists and consultants, with more than 10 years' experience in their field, who were studied in their everyday, real-world work environment and not in an experimental exercise.

We decided to select IT specialists for our study, based on the findings from literature review, showing that the information and communication technology is one of the most "teleworkable" occupation [3]. On the other hand, software consultants need to interact directly with customers, and only some part of their working activity can be performed from the computer. The working habits of these two categories of employees confirmed this diversity in our analysis.

The participants have been notified about the monitoring process, and this is possible to influence their working behavior and routine. Such influences need to be further analyzed with more employees and for longer periods.

We were transparent about the data collected and assured the employees about confidentiality and data anonymization.

For integrity, accuracy and data validation purposes, purposes, two types of data processing were used, and the results were compared to each other, (please see figure 1 and chapter III). The results were also reviewed by the organization, and inconsistencies were removed.

Another limitation could concern the small number of participants, but this concern is balanced by the significant number of records (3.5 million) and number of days (114) monitored. Previous studies in this field reported similar figures, for instance Astromskis *et al.* [30], analyzed the interaction of the six developers with IDE, Minelli *et al.* [31], also presented an analysis based on 5 millions of IDE events, while Meyer *et al.* [34], analyzed a higher number of participants (20), but for a two weeks period.

A generalization of the results is not our purpose to indicate, not even at the industry level, studies with more employees involved and for longer periods would be recommended.

V. CONCLUSION AND FURTHER WORK

The framework and tools proposed in this paper could be a solution for monitoring and evaluating the performance of employees working remotely. The functionality of the framework was evaluated in an IT company, where programmers and software consultants were monitored for 114 days.

By analyzing the interaction with the computer, we described how a typical workday looks like, by introducing types of activities: actual work, documentation, and recreation.

We found how employees perform work-related activities at different time intervals, and what kinds of applications they use. Important conclusions came when analyzing inactive time, defined as long breaks and short breaks, as such results can provide important information about employee productivity and burnout risk. While in our study we monitored both programmers and consultants, we concluded that the workday looks different when analyzing the start and finish periods, types of activities, and the period to perform them.

Another objective of our research was to find if the working habits for teleworking employees are different from the "traditional" one, using such indicators as active time/inactive time, respectively time with work-specific activities. Remote employees are spreading their working program over a broader period, as they have the flexibility to perform other activities during the "normal" program. Time spent with meetings is much shorter in teleworking, and the employees seem to use this time for programming and other related activities.

We did not aim in our research to evaluate employees against output KPIs, such as progress on tasks, quality, and customer satisfaction; further studies can be developed in this field, for understanding why some employees have better results than others. Another interesting direction for future work is to evaluate the impact of remote work on employee satisfaction and work-life balance.

ANNEX 1
KEYWORDS ASSIGNMENT TO ACTIVITIES

Keywords (activity types)	
Actual WORK	„gits"; „eclipse"; „SQL"; „Outlook"; „conta.ini"; „OpenVPN"; „AnyDesk"; „Query(s)"; „WinSCP"; „workspace"; „Zoom"; „Live Mail"; „.xsl"; „Araxis"; „Altova"; „PuTTY"; „Skype"; „Total Commander"; „taskbar"; „Visual"; „explorer"; „Notepad++"; „:: Firma: "; „inbox"; „email"; „Commit"; „Revisal"; „Ammyy"; „WhatsApp"; „java"; „dx_"; „Nomenclator"; „Open Type"; „Planul de conturi"; „Preluare facturi receptie"; „Program Manager"; „sal.ini"; „Save As"; „Task Switching"; „facturi"; „extras"; „xml".
Documentation	„word"; „excel"; „power point"; „Google Chrome"; „Mozilla Thunderbird"; „Mozilla Firefox"; „pdf"; „docx"; „txt"; „Find"; „Replace"; „adobe"; „xls"; „notepad".
Recreation & Informal Learning	„eMAG.ro"; „Facebook"; „aliexpress"; „news"; „autovit"; „olx"; „png"; „Paint"; „yahoo"; „eBay"; „gmail"; „FlashScore"; „Lidl"; „locomotiv"; „Pinterest"; „ProSport"; „trenulet"; „youtube".

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