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An Agent Based Simulation System for Analyzing Stress Regulation Policies at the Workplace

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Abstract

Workplace stress has a significant impact on productivity, since keeping workers' stress on an adequate level results a key factor for companies to increase their performance. While a high stress level may conduct to anxiety or absenteeism, a low level may also have undesirable consequences, such as lack of motivation. To identify and understand all the elements which interfere on workers' stress results a key factor in order to improve workers' performance. However, the complexity of human behavior increases the difficulty of recognizing the influence of these stressors and finding a way to regulate workers' stress. This paper proposes the use of agent-based simulation techniques for addressing the challenge of analyzing workers' behavior and stress regulation policies. The main contributions of the paper are: (i) the definition of a stress model that takes into account work and ambient conditions to calculate the stress and the productivity of workers; (ii) the implementation of this model in an agent-based simulation system, enabling the analysis of workplace stress and productivity for different stress regulation policies; (iii) the analysis of four different stress regulation policies; and (iv) the validation of the model with a sensitivity analysis and with its application to a living lab.

Keywords: stress, agent-based simulation, productivity, stress modeling, workplace stress

1. Introduction

Recent changes in working life have led to new challenges for organizations and employees, which may result in increasingly stressful working environments [1]. The economic and health costs of stressful work environments may be much greater than expected. The Fourth European Working Conditions Survey [2] stated that 22% of Europeans were suffering from stress and fatigue; and in a recent opinion poll, 51% of European workers considered that stress is common in their workplaces [3]. Also, it is estimated that work-related stress is the cause of about the 50% of all lost working days in European enterprises [4]. Similar

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results can be found for United States, where 40% of workers reported their job was very or extremely stressful and 29% of workers felt quite a bit or extremely stressed at work [5].

The huge impact of workplace stress on business has enhanced the interest and research on stress prevention. Work related stress can be prevented if the main provoking factors (or stressors) are identified. This could enable the design and implementation of regulation policies that decrease their adverse effects.

However, evaluating the effectiveness of these policies in a real scenario is challenging, mainly due to two reasons: the complexity of human behavior, and the costs that entails the implementation of stress detection and regulation techniques in a real scenario. These challenges could be addressed with the use of agent-based simulation. Agent-based simulation techniques have an established place in the analysis of human behavior [6], as they provide an approach to evaluate a large number of behavioural dimensions or variables without the need of implementing expensive systems. The use of agent-based simulation is particularly useful when there are complex interactions between agents, heterogeneous populations, and complexes behaviors [7]. One of the open challenges in agent-based systems is the difficulty of designing reliable agent behavior models, due to the high number of variables involved in human behavior [8], which are often hard to quantify, calibrate, and even justify. Focusing on the modelling of workplace stress, there are some approaches [9, 10] in the literature which propose a model based on the working conditions (workload or available time).

This paper aims to advance the state of the art in human stress models, proposing a model that integrates not only working conditions, but also ambient. The model has been implemented in an agent-based simulation system, and evaluated by mean of a sensitivity analysis. In addition, a real experiment in a living lab has been carried out in order to validate the simulation results. The article also provides an open source tool for studying and analyzing different stress regulation policies, measuring their effectiveness for regulating stress and improving workers' productivity. This tool has been used for carrying out an analysis of four different stress regulation policies, whose results are also presented.

The remainder of the article is structured as follows: Section 2 gives an overview of stress theories and current work on stress simulation models. Once existing models have been reviewed, the proposed scenario taken into account for the simulations is presented in Section 3. The definition and implementation of the proposed model model is described in Section 4, while the results obtained for the proposed scenario are described in Section 5. Finally, a evaluation by mean of a sensitivity analysis and an experiment in a living lab is presented in Section 6, and Section 7 describes the conclusions drawn from this paper, as well as possible lines of future work.

2. Background

In this section, an overview of the leading theories about stress modeling is given. Then, current research on agent-based stress simulation is reviewed.

2.1. Stress theories

Stress is one of the most important emotions to analyze in the workplace context, as its adverse effects on an employee have a substantial impact on productivity loss [11]. Fur-

thermore, the significant correlation between mental fatigue and impairment of physical performance in humans has been proved [12].

There is not a universally recognized definition for stress, since this notion is used in different contexts. According to the work of Cox and Griffiths [1, 13, 14], there are three different approaches to the definition of work-related stress: engineering, physiological and psychological. In the engineering approach, the stress is seen as a stimulus of the environment in the form of level of demand. Regarding the physiological, stress can be defined according to the changes that occur in a human under a stress state. Finally, from a psychological point of view, stress is defined as the dynamic process that occurs as an individual interacts with the environment.

In the same way that there are numerous definitions of stress, there are also numerous stress theories [15]. The Person-Environment (P-E) fit theory [16], based on the works by Lewin [17] and Murray [18], has been the source of other approaches to stress and well-being. This theory argues that stress arises not from the person or environment separately, but rather by the fit or congruence between them. It defines stress as a lack of match between their abilities (knowledge and skills) and the demands placed on them.

In 1982, Lazarus & Holroyd proposed the Transactional Model of Stress [19], that considers stress as a relationship between the person and the environment. This environment is appraised by the person as taxing, thus threatening well-being [20]. Lazarus & Holroyd distinguish two types of appraisal: primary and secondary. At the primary, a person acknowledges that there is something at stake; while at the secondary, individuals search for the benefit in a demanding encounter [21].

A different approach is the Job Demands-Control-Support model, proposed by Karasek and Theorell [22]. This model proposes an interaction where high demands and low control would predict high strain, but that high control would buffer the negative effect of demands on outcomes. The model has good predictive validity at the macro level, but it does not take into account individual differences in susceptibility to stressors. Consequently, it cannot explain the different behavioural or health outcomes under the same levels of demand and control in two individuals [23].

Another popular view of stress at work is the Effort-Reward Imbalance (ERI) model, proposed by Siegrist [24]. This model introduces some key features, as it emphasizes subjective perceptions of the environment. The central concept of the ERI model is that effort at work should be compensated by suitable rewards, and a mismatch between them will lead to stressful experiences.

With regards to the impact of stress on work performance, psychologists Robert Yerkes and John Dodson proposed the Yerkes-Dodson Inverted-U law, which is an empirical relationship between stress and performance in an attempt to obtain optimal efficiency from an individual [25]. Yerkes-Dodson Inverted-U law argues that individual performance increases with stress until the moment a limit value is reached, and decreases if this limit is exceeded. This law is often depicted as a normally distributed curve on a graph as seen in Fig. 1.

Fig. 1 shows how as the stress level increases, the individual performance also increases. The individual goes from a state of boredom to a state of increasing attention, until the moment in which arrives to the optimal state. From this level, if the stress continues to

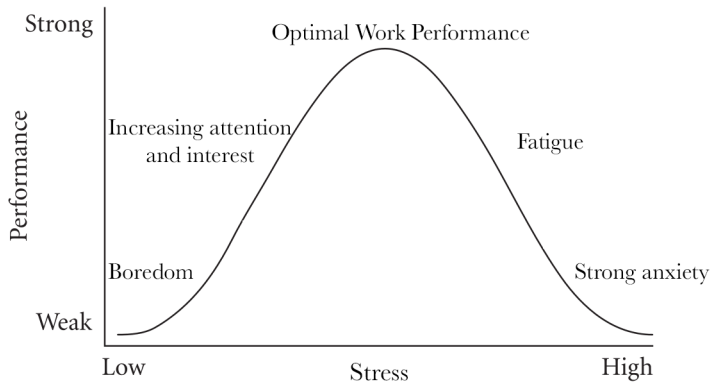

Figure 1: The Yerkes-Dodson Inverted-U pressure performance curve [25]

increase, the individual will enter in a fatigue state and even can arrive to a level of strong anxiety.

2.2. Agent-based simulation of stress

Based on the above theories, different agent-based simulation systems have been designed in order to study stress and its impact on productivity on several scenarios. These systems take into account job-related sources [9, 26]. M. Page [9] proposes a way to calculate the stress factor as a relation between the work hours of an agent in a week (t), the maximum possible work a maximal stress agent will achieve (β) and the rate at which stress impacts an agent's performance (α). This relation is shown in Equation 1. Then, the stress factor is used to calculate the performance.

$$S(t) = \beta + (1 - \beta)\frac{1}{1 + (\alpha t)^2} \tag{1}$$

Instead, the work carried out by M. Duggirala et al. [26] stems from the Silverman's model [27]. This model, which has been particularly defined for modeling human behavior in agents, states that stress is composed of three components: effective fatigue, time pressure, and event stress, as shown in Equation 2.

$$Stress = \frac{EF + ES + TP}{3} \tag{2}$$

Based on this model, different agent-based simulation systems have been proposed for the analysis of different work-related policies. Harshal Hatatnagarkar et al. [28] analyze the implications of using a workload buffering strategy to manage work-related stress; M. Duggirala et al. [26] conclude that understanding the impact of stress can help managers to minimize the risk of crises while maintaining a team. All these solutions assume that all stress components contribute equally to stress.

Silverman's model integrates the classic Yerkes-Dodson Inverted-U model [25] of stimuli and performance with Janis and Mann's taxonomy [29] of coping strategies under stress, in order to develop a rich model describing the integrated stress and performance relationship. As commented in the previous section, the Inverted-U model shows how an optimal arousal level is required for effective performance: if arousal becomes too high, performance decreases.

Our work proposes to advance in the state of the art of agent-based simulation models for work-related stress by including ambient conditions, as well as other work conditions such as working overtime hours or the interruptions caused by electronic communication (email, messaging apps, etc.).

3. Scenario

To better understand the scope of the simulation system proposed, consider the following scenario. DOC is a highly skilled IT SME that detects that the stress level of the workers is too high, and this entails a decrease in their productivity and consequently in the company revenue. The company wants to identify the causes of the increase in the workers' stress level, and to evaluate several regulation policies. Implementing stress level detection techniques and regulation policies in the real scenario entails significant costs for the company, so they decide to address this challenge with agent-based simulation techniques.

With the purpose of analyzing and measuring the effectiveness of different stress regulation policies, the human resources department designs four different policies:

Baseline. It is used as the reference of the current method of operation in the office, and represents the situation to improve. There is not an adaptation nor log system to detect workers' state or ambient parameters. There are several equipment available to adapt the system, such as TV, lights, and Heating, ventilation and air conditioning (HVAC) system. These equipment are manually controlled by the workers, so ambient conditions such as noise, temperature or humidity may not have optimum values.

Ambient Adaptation. This strategy represents an environment where automation of ambient conditions control has been implemented. This guarantees that ambient conditions (such as temperature, humidity or noise) will always be near optimum values.

Workload Adaptation. The environment represented by this policy is an office where workload related tasks have been automated. This allows workers to configure rules that automate some of their daily tasks, which turns out in a relevant time saving and an increase in productivity.

Full Adaptation. This policy represents a whole automated office where there is an adaptation of both ambient and workload conditions.

Workers in DOC follow a schedule with the arriving time to work, the leaving time, the overtime hour limit, the free time and the sleep time. In this way, the activity of workers is

divided into four intervals: working, working overtime hours, free time, and sleep time. In the *working* interval (from 9 a.m. to 5 p.m.), workers will work on the tasks that have been assigned to them and will perform electronic communication related tasks such as reading emails or messages applications. Sometimes they have finished all their tasks, and they can go home earlier. However, there are also days in which they do not complete these tasks before leaving time, so they have to work on them in the overtime interval. This overtime interval may last until 2 hours each day. Once they have finished their tasks or have worked for a maximum of 2 overtime hours, they go home and rest for the remainder of the day.

Following the Inverted-U Theory [25], each worker can be in one of five states depending on the stress level: lame [0, 0.2), inattention [0.2, 0.4), optimal [0.4, 0.6), fatigue [0.6, 0.8) and anxiety [0.8, 1], as can be seen in Fig. 2.

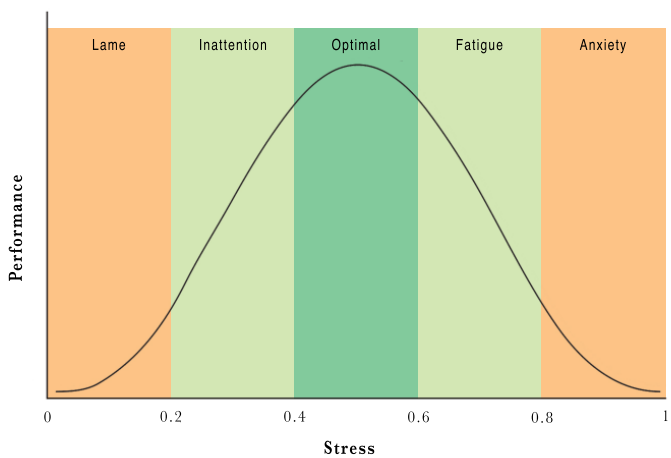

Figure 2: Stress states

A worker with high productivity or performance can carry out more tasks in a shorter period than an agent with a low level of performance. In that way, a worker with a no optimal level of stress may result in absenteeism, that refers to the unscheduled number leaves taken by a worker.

4. Agent-based simulation system

Once the scenario has been clarified, we proceed with the description of the simulation system design. In this section, an agent-based simulation system is proposed for the analysis of stress regulation policies at the workplace. Details about the proposed model and its implementation are given in the following subsections.

4.1. Model definition

The developed stress model is based on the Silverman's stress model [27], which argues that stress consists of three main components: *Event Stress (ES)*, *Time Pressure (TP)*, and

Effective Fatigue (EF). On the basis of this model, we have studied the influence of different ambient and work factors in order to extend it. The diagram shown in Fig. 3 represents an overview of the model design, showing the three components that compose stress along with the features that contribute to them.

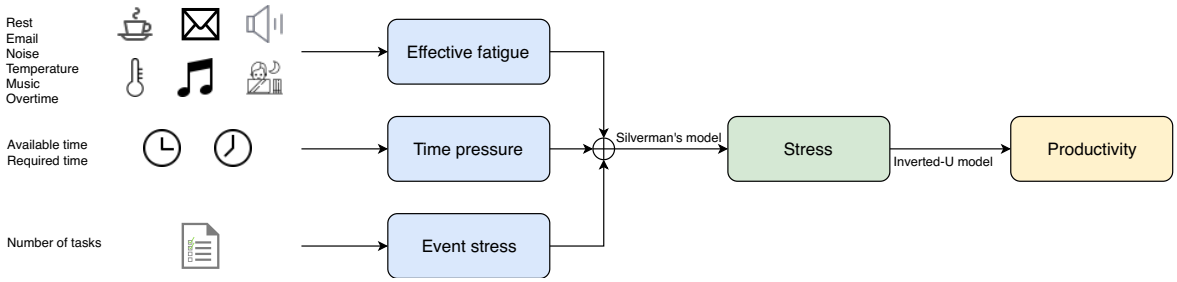

Figure 3: Stress model

As can be seen in the figure, several factors that affect to effective fatigue have been included. These factors are resting, electronic communication, noise, temperature, music and overtime hours, and their contribution to effective fatigue will be described in the following. The stress level is calculated following the Silverman's model from the effective fatigue, time pressure, and event stress. Finally, productivity is calculated from the stress level using the Inverted-U model.

In this work we are considering a workplace scenario in order to measure workers' stress and productivity levels. In this context, *Event Stress* can be attributed to the arrival of a high volume of work, *Time Pressure* to the relation between the time needed to complete the pending tasks in an agent's task queue and the remaining work time, and *Effective Fatigue* to the accumulated tiredness that results of the execution of work-related tasks and the impact of external conditions. Following the assumptions made by related works [26, 28], we assume that all stress components have the same weight in the calculation of the total stress.

$$S = \frac{ES + TP + EF}{3} \tag{3}$$

Silverman's stress model [27] states that all the elements that compound stress can vary between 0 and 1.0, with 0 being over-confident and unstressed, 0.5 neutral, and 1.0 representing the state of maximum stress.

Silverman proposes to calculate *Event Stress* as a relation between the number of tasks received in day and the mean number of tasks to which the worker is used to. This relation is shown in Equation 4, where NT represents the Number of Task per day and MNT the Mean Number of Tasks per day.

$$ES = \frac{\frac{NT}{2}}{MNT} \tag{4}$$

Therefore, if a worker whose average number of daily tasks is 20, one day receives 30, the contribution of ES will be 0.75. In the same way, if another day receives 10, the contribution will be 0.25.

Time Pressure derives from the relation between the required time to perform a task accurately and the available real-time for the task. Silverman represents this relation with Equation 5, according to the work proposed by Hursh and McNally [30]. In this equation, T_i represents the ideal time required to perform a task and T_a represents the available time.

$$TP = \frac{T_i}{(T_i + T_a)} \tag{5}$$

Hence, if an agent has pending tasks whose ideal performing time is 30 minutes, and only makes 20 minutes available, the stress effect of TP will be 0.6.

Lastly, *Effective Fatigue* consists of the contributions of several parameters called Performance Moderator Functions (PMF), that may be positive or negative stressors. Negative stressors are those which increase effective fatigue, and include ambient temperature and humidity, emails or messages received, sleep deprivation, noise, etc. Positive stressors, which decrease effective fatigue, may be relaxing music, video, rest time, etc. Specifically, in this work, the PMFs included will be overtime hours, temperature, humidity, noise, rest time, music and messages received. Silverman calculates EF as a normalized sum of all PMFs as shown in Equation 6, where $WPFM_i$ represents the weight of the PMF, FT_i represents the fatigue tolerance of the agent to the PMF ($0 \leq FT_i \leq 1$), and N represents the number of PMFs.

$$EF = \frac{1}{N}\sum_{i=1}^{N}\left(\overbrace{\frac{WPMF_i}{WPMF_i + FT_i}}^{\text{negative stressors}} - \underbrace{\frac{WPMF_i}{10}}_{\text{positive stressors}}\right) \tag{6}$$

In order to include the most relevant PMFs for the smart office context, the current literature about stress sources has been exhaustively analyzed. The drawn conclusions from this analysis are explained below.

An increase or a decrease of ambient temperature can result in stress for the worker, causing a low-performance capacity. The impact of temperature and humidity on stress can be determined using wet-bulb globe temperature (WBGT) [31]. WBGT is a type of apparent temperature used to estimate the effect of temperature and humidity on humans, whose simplified form, proposed by the Australian Bureau of Meteorology (ABM)[1], can be calculated from ambient temperature (T_a) and water vapor pressure (V_p), as shown in Equation 7.

$$WBGT = 0.567 \cdot T_a + 0.393 \cdot V_p + 3.94 \tag{7}$$

[1]Australian Bureau of Meteorology: www.bom.gov.au

ABM also proposes V_p to be calculated as a function of the temperature and relative humidity (RH), as shown in Equation 8. Relative humidity refers to the amount of the moisture in the air, compared to the potential saturation level. This equation is a

$$V_p = 6.105 \cdot \frac{RH}{100} e^{\frac{17.27 \cdot T_a}{237.7 + T_a}} \tag{8}$$

Studies have demonstrated that the optimal level for the temperature factor is around 24°C with relative humidity of 40% [32], resulting in a WBGT of 22.23°C. In addition, based on [33] it has been estimated that stress level increases between 4 and 9 percent per degree on days when WBGT is above 27°C. If the WBGT level is quite high or low, it will perceived as a negative stressor and will increase effective fatigue. However, if the WBGT level is in the ideal limits, between 20°C and 25°C, it will be perceived as a positive stressor, decreasing effective fatigue.

One way of coping with a demanding work situation is to work longer hours. However, the relationship between fatigue and the number of work hours has been widely documented in past research, demonstrating that overtime and longer working hours result in higher levels of fatigue, errors and lower productivity. Singh et al. [34] use a relation where fatigue level increases around 1% for each overtime working hour, so it will be considered a negative stressor.

Rest breaks have been proposed as a mean of reducing discomfort, indicating that short breaks may be beneficial for worker productivity and well-being at work [35]. Consequently, rest time will be considered a positive stressor that acts as the opposite to work overtime hours.

Numerous research studies have confirmed noise as a primary cause of a reduction in workers productivity, as it is regarded as a source of distraction, frustration, and stress. Besides, it can contribute to stress and illness which, in turn, may produce absenteeism and turnover of staff [36]. Studies show that ideal noise level at work must be between 48 and 52 dBA, and a level greater than 65 dBA involves an important reduction of productivity [37], so high noise levels will be considered as a negative stressor. On the other side, listening to relaxing music before a stress task differently affects biological stress response domains, and helps to recover from a stressor more efficiently [38]. In this way, music will be considered a positive stressor.

Other aspects that affect stress are time management [39] and the pressure of constants notifications [40]. In particular, mail processing has been detected as one of the most stressful aspects in the workplace, as it involves an interruption of the current work. People who daily receive a high number of emails perceive email as a great source of stress, experiencing lower job satisfaction [41] and reporting greater work overload. Kushlev et al. proved that people experienced reduced stress when the number of times they checked their email was limited [42]. Also, email reception affects workers productivity as it involves an interruption of the tasks in which they were working, taking an average of 23 minutes to get back to the task [43]. In addition, nowadays social media and messaging apps have become popular in the workplace, and they also result a way of interruption due to switching contexts. Interruptions that disrupt concentration in a task are often detrimental, and switching tasks

has been associated with higher stress [51]. Following these studies, we model the reception of email or other messages as electronic communication.

With the purpose of designing the model as reliable as possible, the contributions of the explained features to workers stress have been estimated following the explained researches, as shown in Table 1.

Feature	**Contribution**	**Description**	**Source**
Temperature and humidity	If WBGT $\leq$ 20 ºC or WBGT $\geq$ 25 ºC: $WPMF_t = 0.04 \cdot \lvert WBGT - 22 \rvert$	An increase in the difference between the current WBGT and the ideal WBGT (22 ºC) will increase the effective fatigue	E. Somanathan et al. [33]
Overtime hours	$WPMF_o = 0.021 \cdot O_h$	Working overtime hours (O_h) will increase the effective fatigue	M. Singh et al. [34]
Rest time	$WPMF_r = 0.016 \cdot R_t$	Taking a break (R_t) will decrease effective fatigue	A. Dababneh et al. [35]
Noise	If $N_L \geq 65$ dB: $WPMF_n = 0.03 \cdot (N_L - 65)$	If the noise level (N_L) increases over a certain limit (65 dB), the effective fatigue will also increase	L. E. Maxwell [37]
Electronic communication	$WPMF_e = 0.0029 \cdot E_r$	The effective fatigue will increase with the number of emails or messages received (Er)	K. Kushlev et al. [42]

Table 1: Performance Moderator Functions contribution to effective fatigue

The parameters defined in Table 1 influence stress, as they influence effective fatigue. Once the three components of stress are calculated, the stress can be determined. In addition to the calculation of the stress level of the worker, the rate at which this stress impacts worker's productivity results very interesting, as productivity will usually be the feature to maximize in a company. The integration of the Yerkes-Dodson Inverted-U model of stimuli and performance enables the description of the relation between stress and performance. The Inverted-U model shows that in order to achieve the maximum performance it is necessary to have an optimal arousal level. If the arousal level overcomes that optimal level or if it is not high enough, performance will decrease. Following the Inverted-U model [25], the productivity of an agent can be calculated as a function of the stress, as shown in Equation 9, where S represents the stress.

$$P = \frac{1}{0.4 \cdot \sqrt{2 \cdot \pi}} \cdot e^{-\frac{1}{2}(\frac{S-0.5}{0.2})^2} \tag{9}$$

The Equation 9 has been adjusted from the probability density function of a normal distribution $\mathcal{N}(0.5, 0.04)$. The parameters of the normal distribution have been chosen in order to have a function as similar as possible to the proposed by Yerkes-Dodson, limited between 0 and 1 (as the stress level). Productivity (P) will reach the maximum value of 1 when the stress level is 0.5 and will decrease as the value of stress moves away from its optimal value.

4.2. Model development

Once the theoretical aspects of the model have been explained, this subsection describes the development of the simulation system where implementing the simulation model. The simulation system has been designed with the primary purpose of enabling the representation of a smart office in a reliable way. It has been implemented with Python 3.5 using open source libraries. The core of the system has been developed using MESA [44], an open-source Python package that enables the creation of agent-based models using built-in core components or customized implementations. Furthermore, this framework enables the analysis of the results using Python's data analysis tools.

At a high level, the system consists of three main components: (1) a core that provides the simulation services; (2) a data storage component that manages the data generated by the simulation; and (3) a graphical user interface that allows the user to control the experiment execution (starting, pausing, stopping it); selecting parameters (work and ambient conditions, regulation policies, etc.); and executing strategies (number of workers, simulation duration, etc.). The core has been developed using MESA; which provides some base classes for agents, models, visualization and data collection. The user interface has been implemented using Tkinter library[2]. Finally, for the analysis and visualization of the data, Pandas and Matplotlib[3] have been used. In this way, the developed system allows the user to easily configure several aspects about the simulation using the graphical user interface. Once the required parameters have been chosen, the system will create the model and the agents, and the simulation will be run. The system will provide real time data via the graphical interface while the simulation is running, and once it has finished, it will store all the data for its later analysis and visualization.

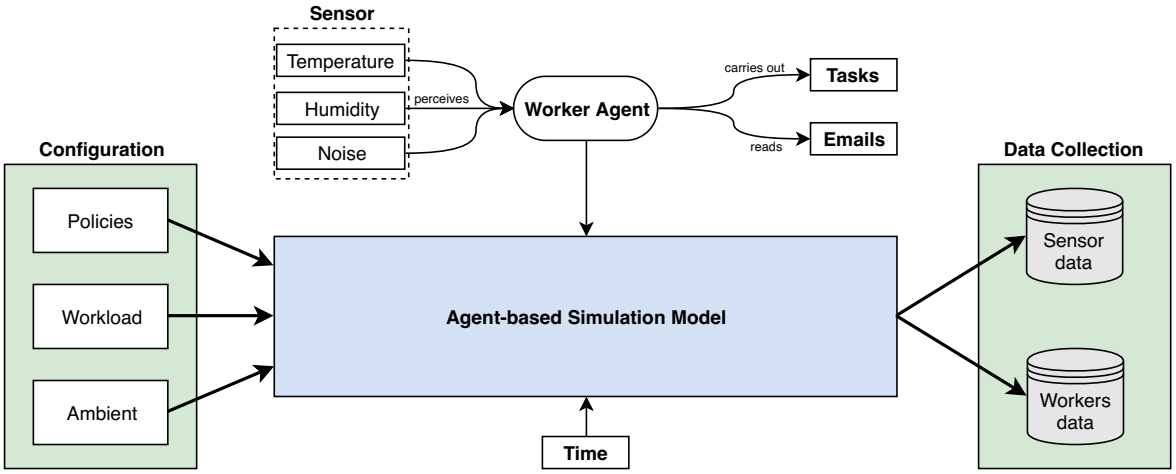

Figure 4: Agent-based simulation system architecture

[2]https://docs.python.org/3/library/tkinter.html
[3]https://matplotlib.org

The proposed system architecture is shown in Fig. 4. The architecture emphasizes on the modularization of the system and on the easy configuration of the different scenarios. The system structure depicted in Fig. 4 shows that the input-data is configurable from a separated module, and the output-data is stored in a repository. This enables an easy configuration of the different scenarios and regulation policies; as well as the data to be extracted from the simulation. In the following, the different modules of the system are described in detail.

The system makes use of two different classes for modelling the entities of the simulation: objects and agents. Tasks, time, sensors and emails/messages are modeled as objects as they do not behave as autonomous entities; while workers are modeled as agents.

Worker agent represents workers of the smart office environment that perform several actions such as carrying out tasks, reading messages or resting. In addition, these agents may suffer from stress when work or ambient conditions are not optimal, resulting in a decrease of their productivity. Fig. 5 shows a diagram with all the actions performed by this agent: at each step, the stress and productivity of the agent are calculated. Then, if it has remaining unread emails or messages, under a certain probability defined in the configuration it reads them during that step. Otherwise, in that step the agent works in tasks or rests depending on the hour and on the pending tasks associated to it.

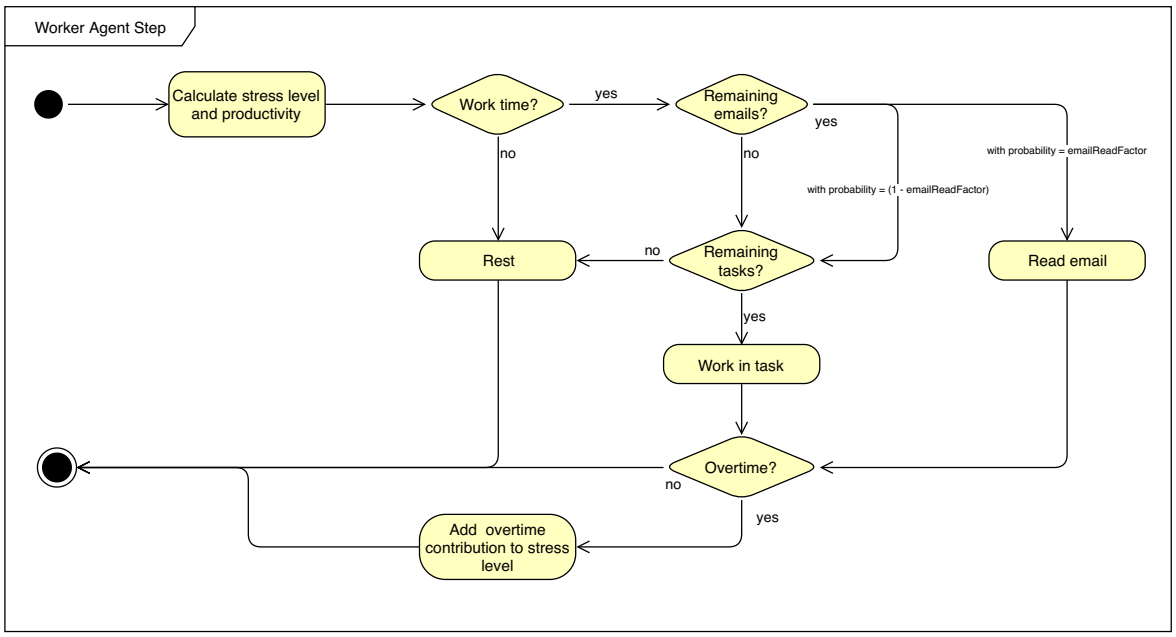

Figure 5: Worker simulation step flowchart

Besides this agent, four objects have been developed for modeling tasks, messages, sensors, and time. These objects represent entities with properties that are relevant for the simulation, and their main properties are listed in Table 2.

- **Task object**. It models the assignments that each worker has to complete, and each one is assigned to a certain worker at a certain time. In addition, they have the estimated and the remaining time required to finish them. Each task has an assignment hour, and they are assigned to each worker along all day. All tasks have an estimated duration of 25 minutes, and the number of them that are commissioned to an agent in one day varies depending on the workload scenario.

- **Email object**. This object represents the reception of emails or other communication messages. Emails are very similar to tasks, they have the reception time and the estimated reading time for each one. The estimation of the number of emails read in a day is based on the work done by Kostadin Kushlev and Elizabeth W. Dunn [42]. This work proposes that the number of emails read in a day follows a normal distribution with parameters $\mathcal{N}(12.54, 8.02)$. The email and message reception is distributed along the day for each worker. The time dedicated to an email by the agent (in minutes) is calculated in function of the time in reading the email (about 25 seconds), the time in answering the email and the time in getting back to the task; resulting in a normal distribution with parameters $\mathcal{N}(3, 0.5)$.

- **Sensor object**. Each sensor is responsible for measuring certain ambient conditions (e.g. temperature, humidity, noise), that are relevant to stress estimation. In order to provide the simulation with a greater reliability, the values for these variables are obtained from real values by mean of the open weather API[4] and the noise dataset generated by The National Institute for Occupational Safety and Health (NIOSH)[5]. This dataset provides several noise levels in different office contexts.

- **Time object**. It provides the simulation with a measuring of the time, converting the simulation steps to time. It has as properties the date and the hour, and methods for defining when a new day or a new hour starts. Finally, also enables the identification of the current interval of the simulation according to the time (working time, overtime or resting).

Object	**Properties**
Task	Estimated time, remaining time, start time, assigned worker
Email	Reading time, remaining time, reception time, assigned worker
Sensor	Temperature, humidity, noise level
Time	Date, hour, is new day, is new hour, interval

Table 2: Objects properties

Once described the agent and objects, we proceed to describe the core of the simulation system: the agent-based simulation model. This module is responsible for managing and coordinating the simulation. It creates and control objects and worker agents, and manages all

[4]Weather API: https://www.apixu.com
[5]Noise dataset: https://www.cdc.gov/niosh/data/datasets/rd-1005-2014-0/default.html

the changes on them. This module gets the simulation settings specified in the configuration (input-data), collects data during the simulation, and store these data at the repositories (output-data). The input-data include the work conditions (required time for each task, tasks arrival distribution, emails and messages reception distribution and the time spent in reading them, etc.); regulation policies; ambient conditions (temperature, humidity, and noise) and general parameters related to the simulation (number of workers, the equivalence in seconds of each step).

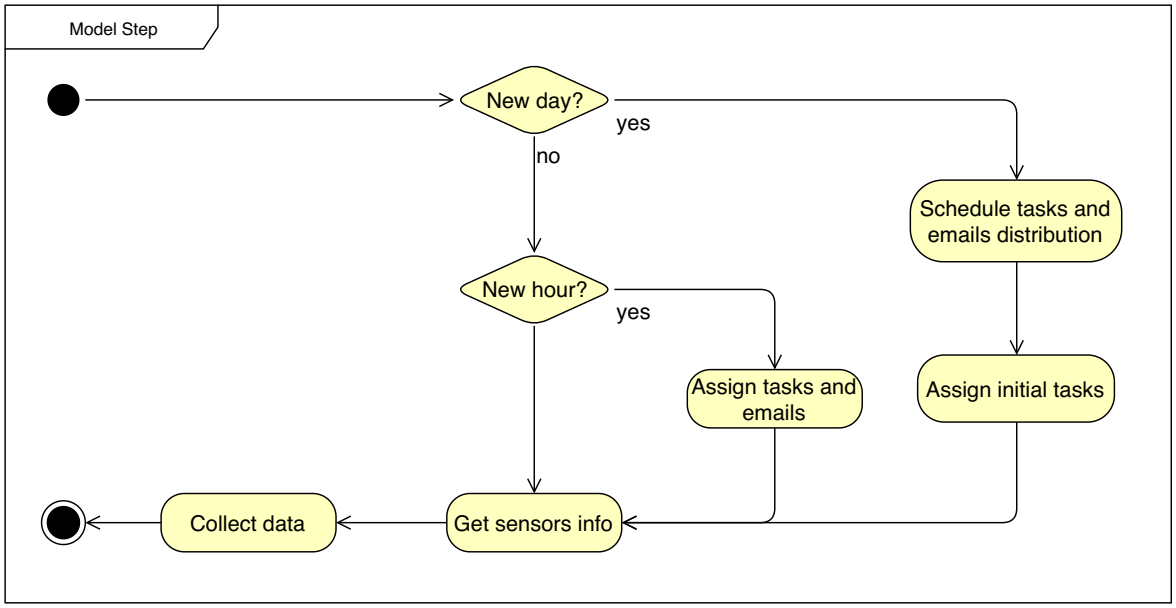

Figure 6: Model simulation step flowchart

Fig. 6 describes the process performed by the model at each step during the simulation. At each step, the model checks if a new day has started. In this case, the model schedules the tasks and email reception distribution for each worker for that day. This defines the reception hour of each task and email. Then, it assigns the initial tasks to each worker.

Every hour, the model assigns tasks and emails to each worker according to the values defined in the scenario; measures the different global parameters (average stress, remaining tasks, etc.) and collects the data. This sequence will be repeated until the simulation is finished. At this moment, the model retrieves the generated data and stores it. The collected data are: stress level (with its three components), ambient data (temperature, humidity and noise), productivity, remaining and finished tasks, read and pending emails, and overtime hours worked.

5. Simulation results

In this section, the results of the simulations run for verifying the effectiveness of the different regulation policies described in Section 3 are presented.

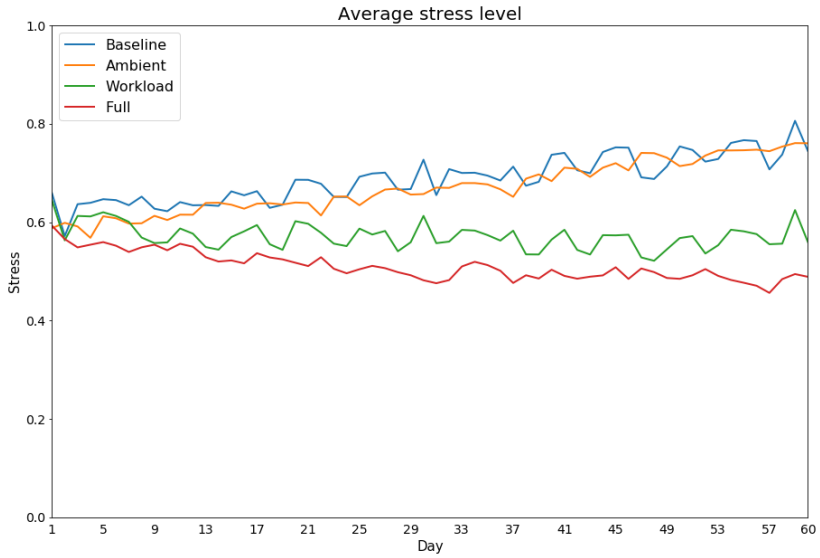

Figure 7: Average stress level of workers for the different regulation policies

The first metric to analyze is the stress level for each regulation policy. The team average level of stress along the two months of simulation is plot in Fig. 7. As shown in this figure, the workload automation policy has better results than the ambient automation. While for the baseline policy the average stress of workers considerably increases during weekdays, reaching values near to 0.8; the full automation policy achieves to stabilize the stress level of workers near to the optimum value. It is also interesting to appreciate how the ambient adaptation results effective for preventing peaks in the stress level, caused by peaks in the ambient conditions.

Analyzing the average values of the stress components for all workers during all the simulation, shown in Fig. 8, the effect of each policy can be appreciated. The figure depicts that while event stress remains stable for all policies, effective fatigue and time pressure are significantly decreased with the regulation policies.

These figures show that from the point of view of reducing stress, the implementation of an automation platform in the office is worth. The automation of both ambient and workload conditions controlling is the best policy to follow. However, seen that the workload automation has a significantly bigger impact that the ambient automation, the company could consider to implement only the former, depending on its budget. Moreover, the simulation also gives some relevant extracted parameters related to productivity, that are shown in Table 3.

The table shows different metrics obtained from the simulation for the different regulation policies, as the average productivity and stress; the average number of unread emails or messages; and the average overtime hours worked; and average number of pending tasks for each worker. As shown, these parameters significantly improve with the application of regulation policies.

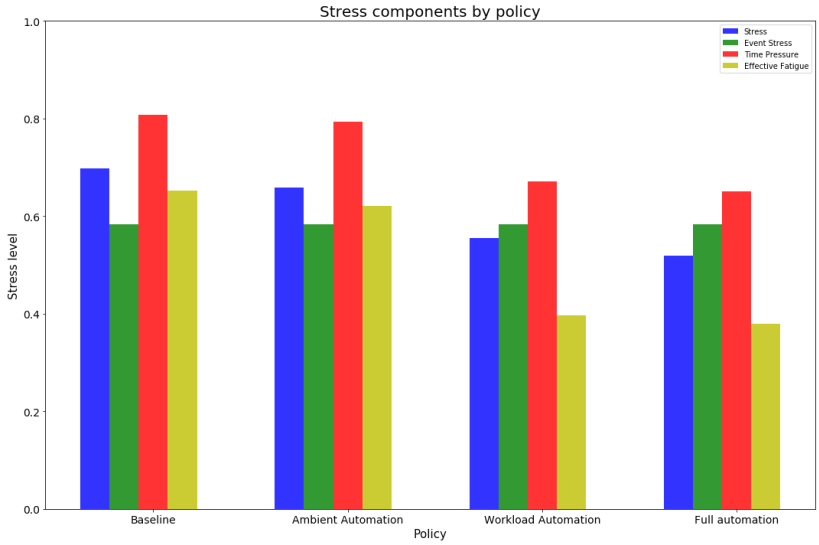

Figure 8: Average stress components levels for each policy

	Baseline	Ambient automation	Workload automation	Full automation
Average productivity (last day)	0.780469	0.793563	0.981176	0.986847
Average productivity (all days)	0.841826	0.870541	0.977049	0.986653
Average stress (last day)	0.753546	0.705455	0.529207	0.510618
Average stress (all days)	0.691424	0.662709	0.563505	0.534662
Average overtime hours	33.925708	33.175153	26.535347	25.945861
Average pending tasks	16.806667	15.369167	5.323333	4.810833

Table 3: Comparison between policies for productivity related parameters

6. Validation

This section describes the conducted experiments that have been carried out with the purpose of validating the proposed model. The system has been validated using two different methods: a sensibility analysis and a real experiment in a living lab. The sensibility analysis has been done with the purpose of identifying the relationship between the involved variables and their effects on the problem; while the real experiment allows us to determine the reliability of the proposed model.

6.1. Sensibility Analysis

The model has been evaluated using two different sensitivity analysis methods: local analysis approach and global analysis. The former studies small input perturbations on the model output, while the later the whole variation range of the inputs [45]. In order to analyze the influence of the different inputs of the system, several scenarios have been defined:

Ambient conditions: three different scenarios have been proposed (low, medium and high temperatures) obtaining temperature and humidity data from an open weather API for different months.

Automation: four scenarios have been defined, representing the four stress regulation policies previously described in Section 3.

Workload scenario: three different scenarios have been proposed, with different workload values (low, medium and high).

To bring about the One-at-Time (or local analysis) method, 100 simulations have been launched considering the different scenarios (10 for each proposed scenario). Fig. 9 shows the results of the local analysis for the average stress level.

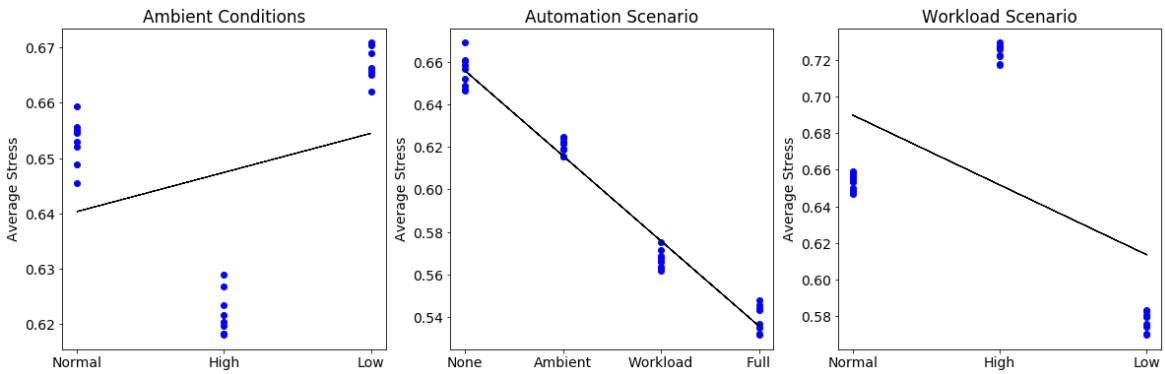

Figure 9: Local analysis applied to the stress level

As can be appreciated, all scenarios significantly influence stress levels. Changes in the ambient conditions have an impact of between 3% and 5% on average stress level. With regards to the automation scenarios, the Fig. 9 shows that while ambient automation only decreases stress between 2% and 4%, workload automation decreases it around a 12%, and the combination of both policies achieves an improvement of near a 15%.

The global analysis has been carried out using Morris method [46], with the SALib library for Python [47]. This method enables the classification of the inputs in three groups: with negligible effects, with large linear effects without interactions and with large non-linear and/or interaction effects [48]. A total of 200 trajectories were built for the model, with the different scenarios described above. The Morris indices are detailed in Table 4. These indices show the influence of the different scenarios on stress level, and state that workload conditions are the variable that has a greater impact on it. Fig. 10 plots these results on a graph, enabling their visual analysis.

Parameter	μ	$\mu*$	σ
Ambient conditions	0.0161784	0.0449908	0.0332322
Workload scenario	-0.0788225	0.167113	0.158649
Automation scenario	-0.112608	0.112608	0.0150309

Table 4: Morris indices for the stress level

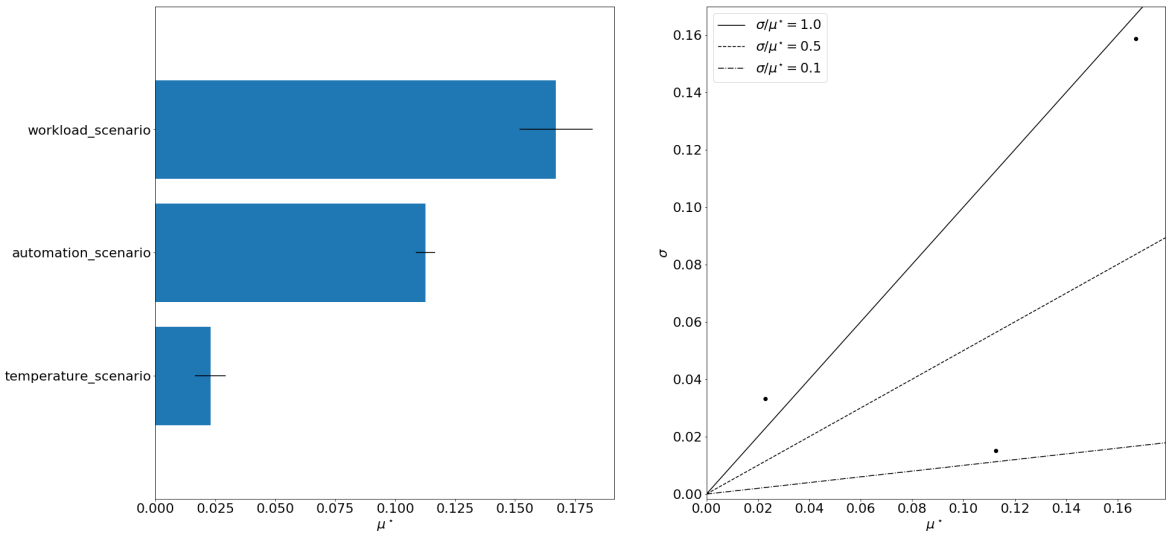

Figure 10: Morris analysis applied to the stress level

The results of the Morris analysis show that the highest $\mu*$ value is for the workload scenario, confirming that it is the most influencer input parameter for the stress. These results also show the importance of the automation scenario, with a $\mu*$ value of 0.11. In the Fig. 10 we can also analyze the ratio $\sigma/\mu*$, that enables the characterization of the input parameters in terms of linearity and monotonicity. Both ambient and workload are non-linear and non-monotonic, while automation is non-linear but monotonic.

The presented methods attempt to validate that the influence that the different input variables have on the output is reasonable with the expected from the model design.

6.2. Experiment

As already stated, the main contribution of this work is the design of a stress model that takes into account ambient and workload conditions, and its implementation in an agent-based simulation system that enables the analysis of different stress regulation policies. For the analysis of these policies, three hypotheses have been raised:

- H1: The use of adaptation techniques helps to regulate stress level of workers who are under stressful conditions.
- H2: The proposed model is reliable and adequate.
- H3: The use of stress regulation policies improves workers productivity.

In order to evaluate the proposed system with respect to these hypotheses, an experiment with real users has been performed. For this experiment, a prototype of the proposed system has been deployed, which includes the following components. The stress of the participants is detected from biometrical signals (by mean of the Empatica E4 wristband)

and a survey. Some actuators implement both hearing and visual signals using a variety of devices. Detailed information on materials is given in Sect. 6.2.2. This section covers the design, results, and conclusions drawn from the experiment, focusing on its scope.

6.2.1. Participants

The experiment included 20 participants. Their ages ranged from 18 to 28 years, all of them university students with a technical background, of both genders. Since the proposed system is primarily oriented to technical work positions, this selection is oriented to validate the system with participants that are currently working in technical environments or will do in the future. With this purpose, the selected participants were fellows in our research group or other research groups in the university. In this way, we tried to simulate the office conditions in order to make the scenario of the experiment as similar as possible to a real scenario. Participants were informed that they were performing an experiment, and provided with detailed information about the data collected in the experiment. However, they were not aware of the purpose of the study in order to exclude the influence of knowledge on the results. The ethical approval for the experiment was obtained by the Ethics Committee of the Technical University of Madrid.

6.2.2. Materials

The material used for this experiment is varied, as the proposed system needs several devices to properly function:

- Empatica E4 wristband[6]. The E4 wristband is a wearable research device that offers real-time physiological data acquisition and software for in-depth analysis and visualization.
- Room lighting (WS2812B LED strip controlled by WeMos ESP8266 board) that is used as an actuator on the light level of the room, with the possibility of using several lighting patterns.
- Google Chromecast [49] that transmits content in a local computer network.
- LG TV 49UJ651V. This device is used for displaying images and videos.
- Google Home. The system uses this device for simulating office noise.

Participants accessed a Jupyter notebook using a computer with the Firefox browser[7].

[6]https://www.empatica.com/research/e4
[7]https://www.mozilla.org/en-US/firefox/desktop/

6.2.3. Procedure

During the experiment, the participants have to complete a total of six tasks, which consist of programming problems obtained from Project Euler[8]. These tasks have an average duration of 5 minutes each one, so participants should be able to resolve all of them in 30 minutes. After the 30 minutes, participants could work on the tasks for other 7 minutes, in order to simulate overtime hours.

Two tasks are assigned to the participant at the beginning of the experiment, while the others are assigned at a certain hour, simulating the task arrival in a real workplace. When a participant finishes a task, he/she gives the response to the evaluator, who checks if the answer is correct and records the time that the participant has spent on the task. If the answer to the task is incorrect, it is given back to the participant. An example of a task is: *"If we list all the natural numbers below 10 that are multiples of 3 or 5, we get 3, 5, 6 and 9. The sum of these multiples is 23. Find the sum of all the multiples of 3 or 5 below 1000"*.

In addition, participants have to perform short but urgent tasks which consist of short questions that must be searched on the Internet, with an estimated duration of 1 minute. These short tasks simulate interruptions such as distractions or email reception. An example of a short task is: *"Which was the release date of the first version of Python?"*.

Also, a questionnaire is given to each participant in three times: at the beginning of the experiment, after 15 minutes and after 30 minutes. This questionnaire is intended to obtain the perceived stress level of each participant, and the raised questions are summarized in Table 5. The questions were designed following a 10-point scale. Different options were studied for the choice selection and, after analyzing the different options, we opted for a 10-point scale. Some of the benefits that we found in the use of a 10-point scale were better variance and better opportunity to detect changes [52]. In addition, the participants in the experiment are used to a 10-point scale, as it is the scale used for the grades in Spain schools and universities).

No.	**Question formulation**
Q1	From 0 to 10, what is your current stress level?
Q2	From 0 to 10, how stressful the number of pending tasks is?
Q3	From 0 to 10, how stressful is the remaining time available for finishing all tasks?
Q4	From 0 to 10, how stressful are current ambient and personal conditions?

Table 5: Questions raised to the participants

At the beginning of the experiment, the Empatica E4 wristband is given to each participant, in order to capture biometric data while they perform the tasks. This biometric data is used for analyzing the stress level of each participant.

The experiment finishes when the participant has completed all the tasks or when the 37 minutes (regular time of 30 minutes plus overtime) have finished.

[8]https://projecteuler.net/

6.2.4. Design

The experiment was a within-subject design. As previously stated, the controlling factor is the use of the adaptation techniques, which has two levels, activated and not activated. The automation use factor is counterbalanced using a Latin square so that the participants are divided into two groups: the control group and the treatment group. Participants in the control group performed the experiment without any kind of adaptation or automation; while participants in the treatment group performed the experiment with the adaptation system enabled. Both groups were formed by the same number of participants.

The workplace scenario consists of a small office, where participants have a computer with an opened Jupyter notebook o in the Firefox browser, where they must resolve the programming problems. In order to simulate office noise, an audio containing 2 hours of office noise[9] is played in the Google Home device. When the adaptation is activated, a relaxing video[10] is cast to the smart tv and the room lighting changes using lighting patterns with coloured lights that slowly vary in intensity and colour.

6.2.5. Results and Discussion

In order to tackle the hypothesis, both biometric data and questionnaire results have been analyzed. The Empatica device provides BVP data extracted from a PPG (Photoplethysmography), the average heart rate (extracted from the BVP signal), and the time between individual heart-beats (IBI data, also extracted from the BVP data). Two features for detecting stress level can be obtained from these data: SDNN (standard deviation of heart rate intervals) and pNN50 (ratio of pairs of successive heart rate intervals that differ by 50 ms or less). On the other side, the questionnaire results provide the perceived stress of participants of the experiment during the performing of the tasks.

The results from the questionnaire show that the stress level in the adaptation part is lower than with no adaptation, as shown in Fig. 11. These results support H1, concluding that users feel more inclined to use the adaptation system rather than performing the task without adaptation. The analysis of the results of this question reveals that users feel more comfortable with the environment adaptation for the completion of the task.

With regards to the biometric analysis, SDNN and pNN50 results can be seen in Fig. 12. The following table, proposed by V.J.Madhuri et al. [50], can be helpful for analyzing the results of SDNN. As shown in the table, a bigger SDNN means a lower stress level, while a lower SDNN means a higher stress level. Our results shown in Fig. 12 show that in the three periods the SDNN has a greater value for the the adaptation scenario. In the case of pRR50, we can see how its value significantly increases during the middle period for the no adaptation scenario, indicating an increase in stress level.

Finally, we present some quantitative data related to the experiment. The average number of tasks finished by the participants is 3.74 for the adaptation scenario, and 2.87 without adaptation; the average time dedicated to each task is of 9.8 minutes for the adaptation sce-

[9]Office noise: https://www.youtube.com/watch?v=D7ZZp8XuUTE

[10]Relaxing video: https://www.youtube.com/watch?v=4inYSp-RWtU

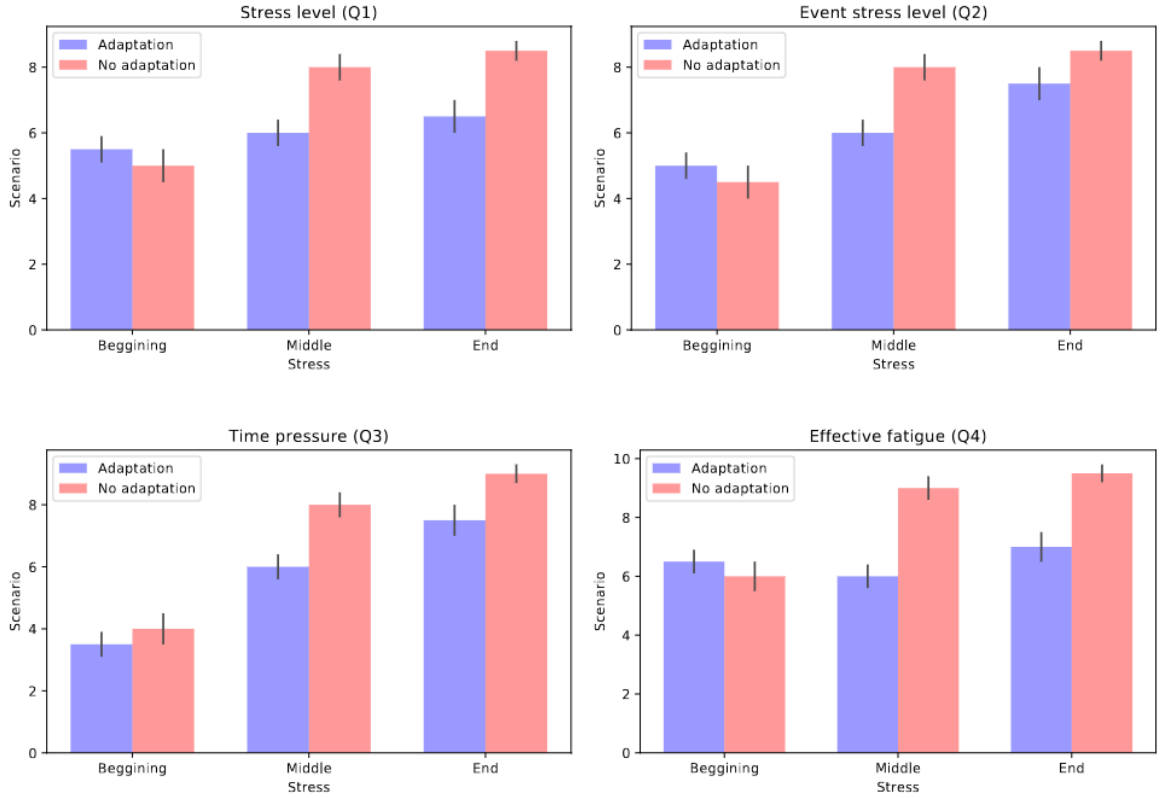

Figure 11: Questionnaire results

SDNN (ms)	Stress level
25-55	Highly Tense
55-110	Slightly Tense
110-180	Midly Calm
180-215	Quietly Relaxed
215-230	Deeply Relaxed

Table 6: Stress level from SDNN [50]

nario and 12.8 for the no adaptation scenario; and the minimum time required to finish a task was of 4 minutes for the adaptation scenario and 6 for the no adaptation scenario.

These results support H1 in the same way that the questionnaire; and also H2, indicating that users' productivity is improved with the use of stress regulation policies. In addition, these results are adequate with the expected from the simulation results, confirming that the use of agent-based simulation can help to identify stress causes, design stress regulation policies, and thus, to prevent stress.

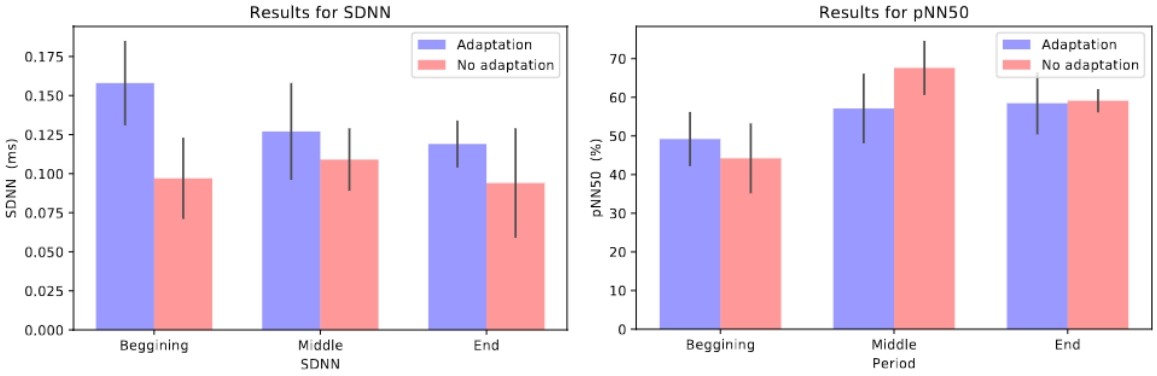

Figure 12: Biometric analysis results

7. Conclusions

In this work, an agent-based simulation system to analyze stress regulation policies at the workplace has been developed. This system implements a stress model also proposed in this paper, that takes into account both workload and ambient conditions for determining stress and productivity levels of workers. The proposed system enables the simulation of a smart office in order to analyze the evolution of workers' stress and productivity over time; and allows users to configure custom adaptation policies in an easy way.

In addition, this paper also shows the result for the analysis of four different stress regulation policies, measuring the influence of different adaptation levels on stress and productivity. These results show that ambient conditions adaptation does not result particularly effective for regulating stress at the workplace by itself, but combined with workload adaptation, it achieves a decrease of a 10% in workers' stress. The sensibility analysis performed to the model confirms this result, showing that between all the variables, the workload condition is the one that affects in a more significant way to stress and productivity. Finally, the results of the experiment in a living lab validates these results. The answers to the self-reported questionnaires demonstrate the positive effect of the adaptation for regulating stress, and also the results obtained from the analysis of the biometric data show that stress levels are lower when there is adaptation.

We are currently exploring some lines of future work that stem from this work. Firstly, we aim at integrating different personalities for the agents that represent the workers, with different ways of coping with the workload and ambient conditions. Also different ways of coping with tasks or messages reception depending on the agents' mood could be studied. Secondly, another possible line of future work that we are currently investigating is the integration of room offices and locations in the model, in order to analyze the stress contagion between workers who work together. Finally, the third line of future work is to improve the validation method with more experiments, increasing the number of participants, and also including a pairwise comparison method in order to improve the accuracy. These advances

would give more reliability to the model.

Acknowledgements

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