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Artificial intelligence to manage workplace bullying

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ABSTRACT

This research links the efficiency of artificial intelligence (AI) to the work climate. The aim is to compare whether workers would feel comfortable dealing with a case of harassment at work with an AI system, or whether they prefer to deal with people. This is a pioneering study, unanswered in the literature. A questionnaire has been applied and a sample of 329 workers was obtained, from which it has been possible to conclude, that in cases where there is a good working environment, they feel more comfortable talking to people than to robots, and vice versa when the working environment is bad. Moreover, it is concluded that when workers trust their human resources (HR) departments, they prefer to deal with people regarding a problem such as bullying and that when they trust AI systems, there is a greater preference to interact with robots than when they do not trust them.

1. Introduction

To define what Artificial Intelligence is, we must take into account that it is a reality in constant evolution. This is clear from the changes proposed for its regularization within the framework of the European Union. In this regard, the Czech presidency of the European Union presented on November 3, 2022 the final version of the proposed AI Regulation, unanimously approved on November 18 of the same year, by the Committee of Permanent Representatives of the Governments of the EU Member States (COREPER) (Pagallo, Ciani Sciolla, & Durante, 2022). This law proposal understands in its article 3.1 that Artificial Intelligence is a system trained to be autonomous and to produce predictions, recommendations or decisions based on the logic of the data. To reach this point, the Artificial Intelligence system requires the intake of data or inputs, provided by people or machines (Schuett, 2023). A final regulatory law is expected to be passed by mid-2023. But to reach this point, as we indicated above, it is the product of an evolution that dates back a long time.

Thus, although some authors already see in Aristotelian logic the first signs of Artificial Intelligence (Belda, 2017), we will highlight the figure of Alan Turing in the twentieth century, who considered that if a machine behaves as an intelligent entity, to the point that its actions are not differentiated from those of a person, by another human being, it should be considered intelligent (Villar-Sepúlveda & Champneys, 2023).

In 1956, eleven of the most brilliant mathematical minds of the time, including Marvin Minsky, creator of the expression Artificial Intelligence, and the psychologist Frank Ros, pioneer of neural networks, among others, met at the Dartmouth meeting (Nieto, 2023). At this meeting, which lasted two months, the two opposing approaches or positions on which the foundations of artificial intelligence are based emerged. One of the currents is the top-down vision of Newel and Simon, for whom cognition is a high-level process, where the brain can be replaced by technology. Therefore, for these authors, artificial intelligence should be oriented towards generating machines capable of carrying out the same symbolic operations as the human mind. On the other hand, there is the botton-up approach, represented by Rosenblatt and very close to Turing's original proposal. The author defended the need to generate hardware that emulates the structure of neuronal connections of the brain and not only its symbolic actions, as proposed by Newel and Simon (Larsen, 2023).

After a period of ups and downs in which both currents obtained some progress, although without fulfilling the expectations generated around this technology, it has been necessary to wait until the second decade of the 21st century for a definitive takeoff, thanks to the irruption of Big Data, data mining and the leap from industry 4.0 to 5.0 (Pizoń & Gola, 2022).

Currently, other authors have taken the baton of Artificial Intelligence and its applications to society. For example, Abduljabbar, Dia,

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Liyanage, and Bagloee (2019) define Artificial Intelligence (AI) as a field of computer science that makes machines work like a human brain and Ginestet (2010) adds that it gives computers access to Big Data and extracts important features to solve complicated problems. Today, the growth and development of AI is exponential and algorithmic and predictive technologies are applied to fields such as healthcare, education, justice, etc. (Crawford & Schultz, 2019; Kuryło et al., 2022). The reasons for this growth are due to three simultaneous developments: better algorithms, increased networked computing power and the technology industry's ability to capture and store massive amounts of data (Campolo, Sanfilippo, Whittaker, & Crawford, 2017).

AI has had a significant impact on different sectors, in particular in the field of transport, with autonomous vehicles and sustainable mobility (Abduljabbar et al., 2019), air traffic and rail traffic (Tumer & Agogino, 2007). In the tourism sector and especially in eTourism (Chuang et al., 2017), digitalisation has changed the rules of the game (Samara, Magnisalis, & Peristeras, 2020).

The financial sector is not far behind either, and most of the current applications of AI belong to the field of machine learning. The mechanism focuses on a computer drawing conclusions from a statistical analysis of data, in a process that improves automatically as more and more information is introduced into the algorithm and allows greater knowledge of the customer (Fernandez, 2019). Chatbots and virtual assistants are frequently used to resolve the most frequent doubts or carry out the most common operations, such as transfers, in the granting of loans and credit assessment, based on the socio-economic data of applicants (Hentzen, Hoffmann, Dolan, & Pala, 2021), in the analysis of customer preferences, or in the prevention of money laundering, detecting anomalies (Biallas & O'Neill, 2020).

The American Medical Association defines the role of AI in healthcare as "augmented intelligence", indicating that AI will be used not to replace but to enhance human intelligence, e.g. in the case of chronic diseases it allows patients to be cared for at home (Chen & Decary, 2020). There are also robots that operate more accurately than humans and perform automated screening. In medicine, AI systems have demonstrated a greater ability than medical specialists to diagnose cancer by reading diagnostic tests.

In addition, in everyday life, people have incorporated different artificial intelligence systems, such as furniture assembly, cleaning systems or voice assistants such as Alexa or Siri (Suárez-Ruiz, Zhou, & Pham, 2018). All these everyday experiences related to AI mean that people already see the relationship with AI systems as something quotidian, normal, effective and safe. Therefore, the relationship of trust between people and AI is already a fact today, and therefore, perhaps we should go a step further and test this relationship in unsatisfactory work situations.

Many authors, especially in the last two years, relate AI to the detection of cyberbullying. This is the case with Rakhmatov (2022), who proposes machine learning to detect cyberbullying, since the bully uses a series of offensive words or expressions that can be identified and then acted upon, or Beltrán, Hernández, Reyes, Flores, and Zepeda (2022), who analyses the impact of various feature extraction methods on machine learning classifiers to improve the performance of cyberbullying detection models.

Our research takes as a starting point the theory of Szewczyk and Janik (2021), who study the extent to which AI can have an emotional component and resemble a human, and as a continuation, the analysis of Cebulla, Szpak, Howell, Knight, and Hussain (2022), who, in view of the integration of AI in organisations, as facilitators of more data sources related to speech or video, facial recognition etc., have promoted a new understanding of the data extracted from the actions of workers, through "Big Data" analysis techniques, such as predictive modelling.

The purpose of this article is to analyse whether the workers of a company, faced with a case of harassment at work, are prepared to deal with it with an AI system, rather than with a person. The issue raised is very innovative, as there are very few existing bibliographical references on the subject. Recently, Contreras, Aguirre, Roldán, Romero, and Cabrera (2022) presented a study for the detection of mobbing cases, based on AI and data mining applied to a transport company. The algorithm used perceived the negativity or positivity of comments in order to extract whether signs of mobbing were occurring. The data was obtained from a blog of anonymous suggestions and complaints, filtered under a sentiment analysis model using Knowledge Discovery in Databases (KDD) and a machine learning system based on artificial neural networks.

The article reviews the main functions that can be replaced by AI, focusing on the HR area, and then introduces the concepts of work climate and job satisfaction, to study workplace harassment as a dysfunction of the same. The quantitative study is then presented based on a sample of 329 workers, with a multiple linear regression analysis using the method of successive steps, and the hypotheses previously put forward are contrasted. It ends with the analysis of the results and the conclusions of the study carried out.

2. Theoretical framework

2.1. AI and people management

Although the implementation of artificial intelligence systems is still limited (Benbya, Davenport, & Pachidi, 2020), the market is increasingly welcoming these technologies. For example, the artificial intelligence-based platform Eightfold, used for talent management, is valued at over \$2 billion (Singh, 2021). Phenom, tasked with automating job tasks and improving the job search experience has also reached a value of more than \$1 billion (Kelly, 2021). Meanwhile, Lunden (2021) talks about Accenture's \$800 million investment in Beamery, a company that offers a staffing operating system that uses machine learning.

A report by the World Economic Forum (2018) (2018) states that it is estimated that 75 million jobs will be destroyed because of the use of AI in economic activities, but that, in turn, 133 million jobs will be generated. Martín-Artiles, Godino, and Molina (2018) state that the new profiles most in demand will be: data analysts, designers, critical thinkers, social intelligence, digital marketing, remote managers, as well as software analysts and developers, cybersecurity, software and AI engineers, digitisation lawyers, Web/CRO analysts, social network experts, among others.

Technological innovation replaced first the driving force then repetitive tasks in an automated way, and is now replacing ad hoc decision making. The people management function, carried out by HR departments in the company, faces a double challenge in the current context. On the one hand, managing the change of people in the company to take on new technologies, and on the other hand, taking on the new technologies themselves in the performance of their own people management functions, i.e. recruitment or training, among others.

From the scientific point of view, according to Jatobá et al. (2019), research on AI applied to HR in the period 2010 to 2018 was scarce until 2017, with a strong growth in 2018, and the main topics investigated have been AI applied to management, team building and, in third place, its application in recruitment or selection.

2.2. AI and the functions of people management

Palos-Sánchez, Baena-Luna, Badicu, and Infante-Moro (2022) have elaborated a bibliographic analysis of the benefits and challenges of artificial intelligence in people management. These authors consider the main advantage of artificial intelligence to be an improvement in the communication channels between employees and the company. On the other hand, among the difficulties to be overcome is the possible dehumanization that this new form of communication between employee and human resources department may generate (Fritts & Cabrera, 2021).

Prikshat, Malik, and Budhwar (2021) have defined the HR function through the lens of AI as augmented human resource management, understood as the ability of people management to be integrated within the enterprise's information management system and using AI tools, all this to improve decision making and problem solving in the field of human resources. As a consequence, this would lead to improved workflows and work processes, as well as administrative routines, and thus to a reduction of labour costs and an increase in productivity and quality of work. Spar and Pletenyuk (2018) found that AI and data analytics are two of the main trends influencing people management in organisations, which, above all, affect recruitment and talent acquisition (Guerra, Danvila-del-Valle, & Suárez, 2023).

The scope for the use of AI in human resources is becoming increasingly broad. According to Hewitt (2018), 41% of people managers say that not applying automation broadly to people management in the company can lead to a reduction in productivity and, therefore, competitiveness in the performance of people functions.

According to the Human Resources Observatory (2018), companies using AI in their HR processes have increased their productivity by around 300%, in recruitment processing, compared to classic recruitment methods.

According to Bolton et al. (2019), in a global survey conducted by KPMG of 1200 senior HR executives from more than 60 countries, less than 20% of the companies represented had made an investment in AI, as of the time of applying the survey, despite nearly two-thirds of HR executives agreeing that HR has undergone or is undergoing a digital transformation. Only 40% of HR leaders say they have a digital roadmap at the company or HR level.

Among the different areas in which artificial intelligence is applied to human resources are: talent search and recruitment, employee performance analysis, career optimization, as well as staff turnover planning (Qamar, Agrawal, Samad, & Chiappetta Jabbour, 2021; Yahia, Hlel, & Colomo-Palacios, 2021).

For Masum, Beh, Azad, and Hoque (2018), the main problem for applying AI systems in people management processes within the company is the lack of information to be able to automate the different work processes in the area. The authors propose an intelligent information system for people management, which helps managers to make better and faster decisions related to people management in the company.

Preuss (2018) argues that AI is being used extensively in recruitment, allowing companies to gain a broader and more integrated view of candidates and their suitability to fill the jobs on offer. The capture of the ideal profiles for companies is based on algorithms powered by AI and Big Data. For example, the Swiss company Lionstep has developed an algorithm that attempts to recreate human behaviour, based on the candidate's digital footprint, in order to compare their suitability for a specific position and company. For its part, Unilever, within the Unilever Future Leader's Programme, has developed a system that combines gamification, Big Data and AI for talent attraction and recruitment (Feloni, 2017).

On another front, AI-based applications have been developed for managing and sifting through large volumes of information in the early stages of recruitment, where management tasks are highly repetitive. One of the best-known examples is Vera, an AI-enabled robot created by two Russian entrepreneurs, Vladimir Sveshnikov and Alexander Uraksin, which is involved in the selection processes of more than 300 companies, including L'Oréal, IKEA and Pepsi. Its algorithm is fed by information about candidates on job portals and, among its tasks, is to virtually interview prospective employees (Scaliter, 2018).

Niehueser and Boak (2020) found that after a person's selection process their productivity increases when AI is applied from several days to just minutes. When a group of professionals who had not yet used the IA programme were asked whether the use of this technology would make it easier to do their job, 64% agreed or strongly agreed with this statement, meaning that there are other factors besides productivity that should be considered.

However, on this promising technological basis, there are positions that see that IA could generate bias and unfairness (Soleimani, Intezari, & Pauleen, 2021), where the work of HR departments will be fundamental to avoid such a circumstance (Raisch & Krakowski, 2021). Therefore, the primary task of HR managers will be to monitor artificial intelligence programs to ensure transparent models of employee support, where their personal and professional privacy and dignity are protected (Varma, Dawkins, & Chaudhuri, 2023).

And all these developments linking AI to HR processes need to be managed with great care because of the ethical connotations they imply from the point of view of data protection and ethics in general. Prikshat, Patel, Varma, and Ishizaka (2022) suggest taking ethical principles into account in this new framework of AI-enhanced HRM.

2.3. *Work climate and job satisfaction*

A fundamental aspect of people management is the work climate of organisations. Climate research examines individuals' subjective perceptions of their work environment and how these perceptions drive their behaviours and attitudes (Schneider, 2000). Numerous studies have shown a positive relationship between work climate, or a friendly work environment, and job satisfaction, and job satisfaction with employee performance (Subarto, Solihin, & Qurbani, 2021). Similarly, mobbing is a decrease in job performance (Gharlegh et al., 2018).

While people management studies work climate, industrial and organisational psychology focuses on job satisfaction, demonstrating its usefulness in predicting organisational efficiency outcomes in terms of performance and work behaviour (Judge, Weiss, Kammeyer-Mueller, & Hullin, 2017). These same authors suggest the importance of studying workers' perception of fairness, which correlates closely with job satisfaction, since in a changing environment with high job turnover, satisfied employees are more likely to be loyal advocates, ambassadors and defenders of their organisations.

As a result of all the analysis carried out, the following hypotheses are proposed for subsequent testing:

- H1: There is a positive relationship between workers with higher job satisfaction and a preference for dealing with bullying situations with others in the company.
- H2: There is a positive relationship between workers with lower job satisfaction and a preference for dealing with bullying situations with AI systems.

2.4. *Harassment at work*

The term *mobbing* was first defined by Konrad Lorenz. The Austrian zoologist and physician observed some harassment behaviours of gregarious animals towards other, larger, solitary species (Lorenz, 1991). Studies on workplace bullying began in the 1980 s in the Nordic countries, where Heinemann (1972) analysed the bullying of groups of children towards others who showed their weakness in solitary behaviour in the school environment.

It was not until Leymann (1990) came up with a first definition of bullying, in which he describes it as a situation experienced by an individual who is subjected to extreme psychological violence. Furthermore, the author considers that for bullying to occur at work, there must be attacks by a group of colleagues, repeated at least once a week and for a period of no less than six months (Leymann, 1996; Fidalgo et al., 2009). As a pioneer in *mobbing* studies, Leymnann classified mobbing activities into five main groups: actions that impact on self-expression and communication; actions that affect opportunities to interact socially; actions that seek to undermine reputation and authority; actions that attack the quality of life and professional life; and, finally, those activities that threaten the health of the victim, where physical aggression and sexual harassment would be included (Leymann, 1996: 170).

Likewise, Duffy and Sperry (2012) affirm that workplace bullying has its origin in a bad way of managing its leadership in charge of the organisation. In this sense, the assignment of tasks based on unattainable objectives (Topa Cantisano, Depolo, & Morales Domínguez, 2007), depriving the worker of responsibilities in exchange for routine activities (Alfano & Fraccaroli, 2009), to make him fall into the silent organisational ostracism (Schechtman, 2008), intentionally leading him/her make a mistake in his/her work to later make him/her responsible, as well as encouraging other colleagues to participate in these activities, are common practices. In other words, the differentiating element in *mobbing* has to do with the intentionality of the bully, a point that leads us to distinguish between *mobbing* and *burnout*.

Hamzaoglu, Yayak, and Turk (2022) consider that *burnout* can be the result of a lack of definition of roles within the company, poor business management, lack of labour resources, or an overload of work, without malicious intent, but which can lead to demotivation, feelings of guilt and other pathologies that may require the use of drugs. In *mobbing*, on the other hand, the aggressors within the company are malicious in their harmful acts towards the harassed. To this should be added the vicissitudes of the work group and the individual characteristics of the worker (Callea, Lo Presti, Mauno, & Urbini, 2019), who may be perceived as an enviable, vulnerable and/or threatening figure by the harassers.

The consequence of such a work environment has an impact on the physical, emotional, psychological and professional health of the victims (Fiset, Al Hajj, & Vongas, 2017). Ausfelder (2002) identifies stress (Sosko, Buntak, & Grgurevic, 2019), imbalances in the autonomic nervous system, irritability, sleep disorders (Zacharová & Bartošovič, 2016), tiredness and weakness as a direct consequence of *mobbing* (Mardanov & Cherry, 2018).

Ascending *mobbing* occurs when a person in a lower hierarchical position in the company becomes a harasser of another worker who occupies a higher position in the company's organisation chart. The horizontal variant is the one that develops between workers of the same rank in the company. Finally, the top-down variant is between superiors and their subordinates (Duffy & Sperry, 2012).

Once harassment has been detected, the organisation can intervene in two directions. Either it carries out an investigation of the facts in order to rule accordingly, or it can allow itself to be stigmatised, where the harassed person is held responsible for the situation he or she is experiencing. For the company, the consequences are detrimental, because a bad working environment, which is a breeding ground for bullying, leads to absenteeism, disengagement, reduced commitment, and a higher number of accidents at work among its employees (Rasool, Wang, Zhang, & Samma, 2020).

We are, therefore, faced with a situation that companies must often try to solve and prevent with informative policies that delimit in their codes of ethics those activities that constitute workplace bullying (Coyne, Chong, Seigne, & Randall, 2003). This is where Corporate Social Responsibility (CSR) (Vveinhardt & Sroka, 2020) comes into play as a guarantor of the ethical, economic and legal responsibilities of the parties involved in workplace bullying, for the benefit of the social good (Androniceanu, 2019). Along these lines, training and awareness-raising programmes for workers should be carried out. All of this, from a transparent stance in which the protocols and bodies responsible for investigating complaints of *mobbing* must be clear. Steele and Cleverdon (2013) see internal CSR as a very useful tool for managers, as it allows them to build more sustainable strategies, which are perceived as value propositions by workers (Ferreira & de Oliveira, 2014).

However, according to Šoljan, Josipović-Jelić, and Jelić Kiš (2008), conflicts within companies are almost inevitable. Therefore, management must try to detect and resolve them before they can trigger repeated and prolonged physical and psychological abuse. AI has therefore become a new ally in the process. This leads to our next hypothesis:

- H3: Working in friendly work environments is positively related to a preference for dealing with workplace bullying with people in the organisation.

However, this trust in the company and its management team is not always possible, either because of the complexity of the situation or because of the limitations of the management team or the employee themselves. On the other hand, in a changing society, where Industry 4.0 has given rise to an economy based on new production models, it is necessary to streamline the processes of managing, attracting and retaining talent. Hence, with a view to the possibilities offered by AI, we believe it is necessary, within the delicate situation of *mobbing*, to use this type of technology extensively. On the other hand, human communication is complex and combines words, tones and gestures of a complex and sometimes contradictory nature that make it difficult to receive the right message. Xiao, Zhang, Beck, Yuan, and Thalmann (2014) conducted an experiment to demonstrate the ability of a robot to accurately capture certain human gestures in real time. Vishwanath, Singh, Chua, Dauwels, and Magnenat-Thalmann (2019) conducted an experiment in an insurance company with the humanoid robot Nadine, and after one month the workers were satisfied with the interaction and very likely to extend the experience. This is why, among other aspects, the object of the study is to compare the degree of acceptance of this new business approach in the management of employee problems. As a result of all the analysis carried out, the following research hypothesis is proposed:

- H4: Working in hostile work environments is positively related to a preference for dealing with harassment at work with AI systems.

There are numerous experiments that analyse tasks that are currently performed by humans and that can be easily replaced by artificial intelligence systems. One of the examples is the experiment conducted by Suárez-Ruiz et al. (2018) in relation to the assembly of IKEA furniture, a task that has been carried out in a simple way by robots. This should be nothing special, as the assembly of any IKEA furniture follows a standard process perfectly detailed in the instructions. For humans, inexperienced in differentiating between the L1 and L2 screw, it is sometimes complex, but for an AI system like a robot, the part codes are unmistakable.

The same applies to the robots we use at home to vacuum dust. Until very recently, the number of variables required to perform vacuuming correctly was impossible for a machine, so human labour was required. Today, much progress has been made in this direction, and robots are able to adapt to different spaces, furniture, and can overcome certain heights, which has made the use of cleaning robots commonplace in the home. However, they are still far from completely replacing human labour. For example, they cannot move furniture, they cannot climb stairs, among many other limitations.

According to Kruse, Wunderlich, and Beck (2019), the value chain of financial services institutions could be almost completely digitised, meaning that they are processes with administrative routines involving a finite number of variables, measurable and predictable interrelationships through certain algorithms.

Robots and computer programs are known to have beaten world chess champions, such as Deep Blue, which beat Gari Kasparov in 1996, or Alphazero, which is currently in use (McGrath et al., 2021). In medicine, AI systems have demonstrated a greater ability than medical specialists to diagnose cancer by reading diagnostic tests. As another example, Microsoft has developed the Inner Eye program, which automatically highlights tumours and differentiates them from healthy organs based on patient scans, reducing the time it takes doctors to prepare radiotherapy treatment by up to 90% (Álvarez et al., 2022).

According to Kaplan and Haenlein (2020), AI can be found in three different types of systems, according to their level of development. On the one hand, we find human-inspired analytics and humanised artificial intelligence. Analytics is related to the ability to make decisions with learning that has been achieved in the past. Human-inspired AI includes analytical AI related to cognitive intelligence and attempts to incorporate aspects of emotional intelligence into decision-making, such as tastes, preferences and moods. Finally, humanised AI, in addition to incorporating the potential of the previous two stages of AI development, attempts to incorporate social intelligence. That is, it seeks to incorporate the ability to be aware of itself and its interactions with others into the decision-making process.

At this point, we must focus on the degree of trustworthiness that these new technologies bring to the population. There are advocates of computational trustworthiness who are committed to a relationship of human–AI trust. In this sense, Lynn, Mooney, der Werff, and Fox (2020) already spoke a decade ago of e-trust to refer to the interactions that occur in digitally mediated spaces, where the individual is forced to trust digital assistants, such as browsers and wearables, among others. However, the use of AI limits, due to its diversity of agents, the identification of a target in which to place trust. Littlewood and Strigini (2000) argue for multiplicity and complementarity between people and machines. These authors conclude that while AI cannot be trusted as a technological tool, it must be trusted as a system that involves both machine and individual.

This is why it is considered necessary in this work to go a step further and test this relationship in non-routine situations, such as unsatisfactory work situations related to harassment at work. In this sense, there are precedents of robotic mediation in the field of law, for situations with an emotional involvement. For example, the electronic company iCan System was the first company to resolve a dispute with a British court through an AI (Hyde, n.d.). Based on the same technology, a group of Australian mediators has created a tool to manage divorces without going to court (Faes, 2020). In Australia, CSIRO's Data 61 group has devised a method, called a "deep learning neural network", capable of detecting and exploiting vulnerabilities extracted from the way individuals make decisions (Connell, n.d.). The handicap to be overcome with this type of AI-generated action, as with people management in HR departments, is to make up for aspects such as trust and the generation of empathy inherent to human social processes (Staff, 2021), mistrust that generates certain legislative ambiguities. Thus, Article 22 of the General Data Protection Regulation EU (2016) 679 states that every data subject shall have the right not to be subject to a decision based on automated processing by a robot judge. However, in the following paragraph it states that the previous paragraph shall not apply if the law of the Member State in which it is intended to apply can guarantee the rights and freedoms of the data subject, a reaction that aligns with the role theory (Solomon, Surprenant, Czepiel, & Gutman, 1985) and the paradigm of disconfirmation of expectations (McKinney, Yoon, & Zahedi, 2002). Role theory asserts that the individual acts according to previously established social patterns. If the situation experienced coincides with these patterns, there is role congruence and acceptance of the situation. If this is not the case, the authors speak of role conflict and, as a consequence, a rejection of the experience at that moment. As a consequence, the user generates expectations, which he/she compares with the service he/she is receiving. Thus, according to whether this expectation of an outcome is met or not met, there will be a confirmation or disconfirmation, respectively. Two principles are used by Stock and Merkle (2018) to analyse the degree of customer trust in human-robot relationships, applied to the service sector. The authors analyse the customer service of an artificially intelligent robot through the reported experiences of hotel users. The conclusion to their work confirms a positive response to the innovative service proposed by the social robot, although this is lower than the evaluation of the human-human relationship in the performance of the same function. This leads to the following hypothesis:

- H5: Employees' trust in HR departments is positively related to their preference to deal with a situation of harassment at work with individuals.

In view of the above, trust seems to be a key factor in the implementation of AI in society. The everyday experiences related to AI mean that, sometimes even unconsciously, people already see the relationship with AI systems as something quotidian, normal, effective and safe. However, in more complex aspects, outside the quotidian, we align ourselves with Luhman (2017) in considering that familiarity and trust must be cemented on legal strategies elaborated by institutions and the political and social order. In Europe, progress is already being made in this direction. In 2021, the EU proposed a new regulatory proposal on AI, adapted to the risks that may arise from it, as a step towards its full implementation in society. It also advocates a transparent system, under human control and with the supervision of competent authorities, in order to ensure the use of bias-free data and to pay special attention to its use as a remote biometric identifier (Proposal for a Regulation of the European Parliament and of the Council of 21 April 2021 on Artificial Intelligence). Hypothesis 6 is proposed:

- H6: Workers' trust in AI systems influences their preference to deal with a situation of workplace harassment with robots.

The hypotheses are summarised graphically below (Fig. 1).

3. Methods and sampling

The objective of this research is to explore which aspects of the work context and perceptions of AI systems affect the preference of workers to face workplace harassment with interlocutors who are people or AI systems, for example, robots. The six hypotheses indicated above have been raised:

3.1. Participants

Selection of participants.

To select the sample, a snowball system has been used; the type of sampling was non-probabilistic for convenience. The questionnaires were sent to people from different sectors, companies and positions within the company, so that, in turn, they sent it to their colleagues. On the other hand, the questionnaire was shared on the social network LinkedIn, among more than 10,000 professional contacts, as well as other studies or previous work consulted, such as, for example, the following: Acevedo Saavedra, A. G., & Ganoza Cortés, M. P. Adaptación del Instrumento Luxembourg Workplace Mobbing Scale en Personal Administrativo de Empresas del Sector Privado en Lima Metropolitana; Dusek, G., Yurova, Y., & Ruppel, C. P. (2015). Using social media and targeted snowball sampling to survey a hard-to-reach population: A case study. *International Journal of doctoral studies*, *10*, 279; Georgo PhD, M. C. (2021). Media Depictions of Workplace Bullying; Manis, K. T., & Choi, D. (2019). The virtual reality hardware acceptance model (VR-HAM): Extending and individuating the technology acceptance model (TAM) for virtual reality hardware. *Journal of Business Research*, 100, 503–513; Pearce, W., Niederer, S., Özkula, S. M., & Sánchez Querubín, N. (2019). The social media life of climate change: Platforms, publics, and future imaginaries. Wiley interdisciplinary reviews: Climate change, 10(2), e569; Pejic-Bach, M., Bertoncel, T., Meško, M., & Krstić, Ž. (2020). Text mining of industry 4.0 job advertisements. *International Journal of Information Management*, 50, 416–431; Sachini, E., Bouras, N., & Karampekios, N. (2022). Lessons for science and technology policy? Probing the Linkedin network of an RDI organisation. *SN Social Sciences*, 2(12), 1–26; Scott, S., Hughes, P., Hodgkinson, I., & Kraus, S. (2019). Technology adoption factors in the digitization of popular culture: Analyzing the online gambling market. *Technological Forecasting and Social Change*, 148, 119717 or Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, 142(2), 487–498.

It was established, as a criterion for inclusion, that they were persons of working age; and, as an exclusion criterion, that they were people

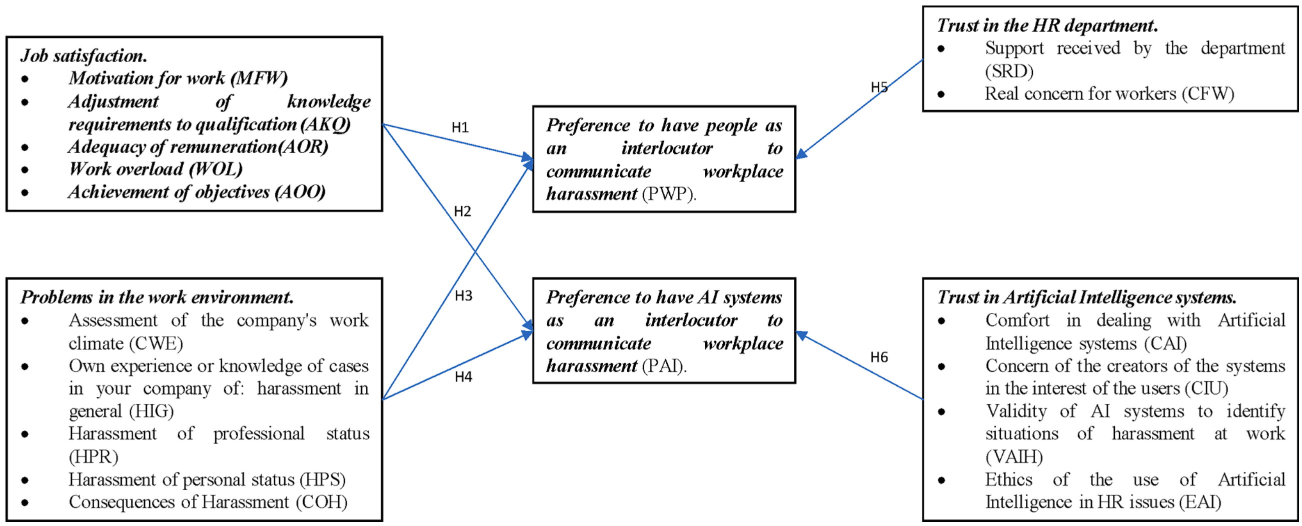

Fig. 1. Flowchart that summarises the presented hypotheses and their link.

who had been linked to the entities in which the researchers work. The participants were sent a link that through the Microsoft Forms application allowed them to complete the research questionnaire anonymously and in which the objective of this was explained.

Finally, 346 correctly completed questionnaires were obtained. After the previous analysis of the data, 17 were eliminated, leaving the final sample composed of 329 participants. Data collection was carried out between September 19 and October 19, 2022. The completion time of the questionnaire was approximately five minutes.

3.2. Description of the sample

The sample of 329 participants consisted, as shown in Table 1, of 55% female and 45% male. In terms of age, 8.5% were between 18 and 25 years old, 28.3% between 26 and 35, 25.8% between 36 and 45, 26.1% between 46 and 55 and 11.3% were over 55 years old. And in terms of the position they held, 52.3% were skilled specialists, 30.6% were middle managers, 9.8% held unskilled jobs and 7.3% held general management positions.

The main advantage of the sample is that it is representative of the population to be studied. The number of responses obtained is like studies on work climate or the use of robots. For example, McMurray and Scott (2003) use a sample of 20 academic staff, Iljins, Skvarciany, and Gaile-Sarkane (2015) use a sample of 49, Churchill, Ford, and Walker (1976), 265 workers, Kim and Park (2020), 282, Berberoglu (2018), 212, Asio and Jimenez (2020), 65, Gaviria-Rivera and Lopez-Zapata (2019), 185, Lan, Huang, Kao, and Wang (2020), 101, Willis, Reynolds, and Lee (2019), 281, Shbail and Shbail (2020), 78, Osmani, Sejdiu, and Jusufi (2022), 200, Ravina-Ripoll, Romero-Rodríguez, and Ahumada-Tello (2021), 190, Van Pinxteren, Wetzels, Rüger, Pluymaekers, and Wetzels (2019), 114, Huang and Liu (2022), 189, Mende et al. (2019), 80, Crompton, Gregory, and Burke (2018), 56, Belanche, Casaló, and Flavián (2020), 168 and Stock and Merkle (2018), 132.

However, it would be desirable to have more responses to ensure to ensure that the results can be generalised.

Table 1
Sociodemographic data of the people interviewed.

Total sample	329
Men	45%
Women	55%
Age	
18–25	8.50%
26–35	28.30%
36–45	25.80%
46–55	26.10%
Older than 55	11.30%
Qualification	
Qualified specialist	52.30%
Middle management	30.60%
Unskilled worker	9.80%
General management	7.30%

Source: Authors.

3.3. Instrument and variables

The questionnaire shall be the measuring instrument used in the research. The format of each of the questions and scales used varies depending on the variable under study. For the sociodemographic characteristics, direct questions, indirect and assessment questions have been used for the variables used in the model.

Perceptions of AI and harassment at work were measured using the Likert scale as used by other authors such as Brougham and Haar (2018) and by Vishwanath et al. (2019). All scales directly measure the perception of the interviewees about specific experiences related to AI and harassment, both their own and those of people around them. The scale goes to zero to ten, where values close to zero identify the low occurrence of the event asked and those close to ten reflect the high occurrence of the asked event, such as What is the motivation for your work for work (MT) (0 = Totally unmotivated to 10 = Fully motivated)?

After an exhaustive review of the literature, a series of items related to workplace harassment, the acceptance of AI in companies and the management of HR in organisations were selected, which had previously been used in other research in these areas. With them, a structured questionnaire of 23 items was designed with which the following variables have been defined in Table 2.

The questionnaire also included five items related to the sociodemographic characteristics and the company in which the participants work (gender, age, size of their company, sector of activity and position they work). The questions in the questionnaire are then related to the existing literature (see Table 2).

An analysis has been performed to assess the validity of the scales used to measure the independent variables (Kerlinger & Lee, 2001). Validity aims to know the degree to which a measurement is free of total measurement error, which at the same time consists of systematic error and random error. Reliability, on the other hand, refers only to the degree to which the measurement process is free of random error.

Table 2
Areas and variables of the research model. Relationship between variables, survey questions and existing literature.

Job satisfaction	What is the level of motivation you feel for your work?	MFW	Scale: 0 = Totally unmotivated to 10 = Fully motivated.	Muñoz-Seco, Coll-Benejam, Torrent-Quetglas, and Linares-Pou (2006).
	Do the skills of your job match your qualification?	AKQ	Scale: 0 = Strongly disagree to 10 = Strongly agree	Adapted from: From, Nordström, Wilde-Larsson, and Johansson (2013).
	Do you consider your level of remuneration to be adequate? (AOR)	AOR	Scale: 0 = Strongly disagree at 10 = Strongly agree	Adapted from: Calvin (2017).
	Have you felt overworked (e.g. undue pressure, impossible deadlines and unnecessary interruptions), or have you been given meaningless tasks?	WOL	Scale: 0 = Never to 10 = Many times	Crick and Grotpeter (1995).
	To what extent do you think you achieve the objectives and results of the work expected in your company?	AOO	Scale: 0 = Very little and 10 = Completely	Cullen, Victor, and Bronson (1993).
Problems in the work environment	How would you rate the work environment of your company?	CWE	Scale: 0 = Very bad and 10 = Very good	Adapted from: Appelbaum, Lee, Amendola, Dodson, and Kaplan (2019).
	Have you ever felt (or know anyone in your company who has ever felt) in your workplace, intimidation, public humiliation, offensive insults or social exclusion?	HIG	Scale: 0 = Strongly disagree and 10 = Strongly agree	Niedl (1996).
	Have you felt, or know anyone in your company who has ever felt threat to your professional status, for example, a derogatory opinion, public professional humiliation, or accusation of lack of effort?	HPR	Scale: 0 = Strongly disagree and 10 = Strongly agree	Rayner and Höel (1997).
	Have you felt, or know anyone in your company who has ever felt threat to your personal position, for example, insults, intimidation or negative references in relation to your age?	HPS	Scale: 0 = Strongly disagree and 10 = Strongly agree	Rayner and Höel (1997).
		COH	Scale: 0 = Strongly disagree and 10 = Strongly agree	Rayner and Höel (1997).
Trust in the HR department	When you have had doubts or required support, do you feel that the HR/ Personnel department offers you the necessary help?	SRD	Scale: 0 = No help to 10 = All the help requested	Rayner and Höel (1997).
	Do you think that in the HR / Personnel department or failing that, the management, really care about the workers of the organisation?	CFW	Scale: 0 = Not worried and 10 = Worries a lot	Cullen et al. (1993).
Trust in Artificial Intelligence systems	Would you feel comfortable and relaxed talking to an artificial intelligence system, for example, a robot?	CAI	Scale: 0 = Very uncomfortable to 10 = Very comfortable	Adapted from: Rosenberg, Nygård, and Kottorp (2009).
	Organizations involved in the development of artificial intelligence take into account the needs, thoughts and feelings of their users.	CIU	Scale: 0 = Strongly disagree and 10 = Strongly agree	Adapted from: Vallor (2016).
	Professionally supervised AI systems (e.g., robots or humanoids) are safe enough to use to identify workplace harassment.	VAIH	Scale: 0 = Strongly disagree and 10 = Strongly agree	Bethel et al. (2016).
	Do you consider that artificial intelligence systems, for example, a robot, applied to Human Resources are ethical?	EAI	Scale: 0 = Strongly disagree and 10 = Strongly agree	Adapted from: Vallor (2016).
Preference to have people	If I were to experience	PWP	Scale: 0 = Strongly	Adapted from: Perez-

(continued on next page)

Table 2 (*continued*)

as an interlocutor to communicate workplace harassment	workplace harassment, would I prefer to tell a human resources/staff person at my company?		disagree and 10 = Strongly agree	Larrazabal and Topa Cantisano (2016)
Preference to have AI systems as an interlocutor to communicate workplace harassment	If you were harassed at work, would you prefer to tell an artificial intelligence system, for example, a robot?	PAI	Scale: 0 = Strongly disagree and 10 = Strongly agree	Adapted from: Beltrán et al. (2022).

Source: Authors.

To ensure the validity and reliability of the data, we proceeded as follows. First, the survey was designed based on models previously applied and validated in research conducted by different authors. However, the research carried out aims to broaden the framework of analysis, so additional filters were applied to verify validity and reliability (Newbold, 1998).

The designed survey was subjected to the critical analysis of five expert researchers in the field. Once the recommendations of the experts were incorporated, a pilot test was carried out on 25 workers, who at the end of the test expressed their opinions on the questions with some doubt. The test passed the test satisfactorily, so it can be said that the questions allow exact and certain answers to be given. The other systematic error, the non-response, was not significant.

3.4. Data analysis

First, a descriptive analysis of the study variables was performed. Subsequently, to know if the aspects of the work context and the perceptions of AI systems influence the preferences of interlocutors to assess harassment, multiple linear regression analysis was applied using the method of successive steps. The stated significance value is <0.05. Data analyses were performed with the statistical package SPSS, version 25.0.

4. Results

4.1 Descriptive results of professional satisfaction, problems of the work environment, trust in HR and AI, and the preference to tell situations of harassment to people and AI systems

Tables 4, 5 and 6 show the descriptive statistics of the variables that participated in the study. Regarding job satisfaction (Table 3), the scores for motivation, adjustment of qualifications to the work performed and fulfillment of work objectives are the aspects in which the participants obtained the highest scores. Regarding the problems detected in their professional environment (Table 3), the participants consider that the work environment in the companies is quite good; however, the scores for the perception in themselves or in their colleagues of the consequences of having suffered some degree of harassment at work are considerable (see Table 7).

Table 4 shows that workers' levels of trust in HR people reach values around six (out of 10) while trust scores in AI systems are close to five (out of 10). However, when they value the concern they believe both (people and AI systems) have for workers, the scores show quite similar values (5.68 and 5.50 respectively).

Table 5 shows that the preference of participants to share situations of workplace harassment is three points higher in the case of people in the organisation versus AI systems.

Table 3
Descriptive statistics of professional satisfaction and problems of the work environment of the participants.

	N	M	SD	Min	Max
Job satisfaction					
MFW	329	7.42	2.07	0	10
AKQ	327	7.46	2.37	0	10
AOR	329	6.20	2.62	0	10
WOL	329	6.36	2.95	0	10
AOO	328	8.13	1.33	2	10
Problems of the work environment					
CWE	329	7.22	2.20	0	10
HIG	326	3.28	3.27	0	10
HPR	329	3.75	3.30	0	10
HPS	329	2.53	2.97	0	10
COH	328	4.70	3.30	0	10

Note. M = Mean; *SD* = Standard deviation; *Min* = Minimum; *Max* = Maximum; MFW = Motivation for work; AKQ = Adequacy of qualification; AOR = Adequacy of remuneration; WOL = Work overload; AOO = Achievement of objectives; CWE = Work environment; HIG = General harassment; HPR = Harassment of professional status; HPS = Harassment of personal status; COH = Consequences of harassment.

Table 4
Descriptive statistics of participants' trust in HR and AI systems.

	N	M	SD	Min	Max
Trust in HR					
SRD	328	6.13	2.91	0	10
CFW	329	5.68	3.02	0	10
Trust in AI systems					
CAI	327	4.87	3.03	0	10
CIU	323	5.50	2.54	0	10
VAIH	323	4.81	2.80	0	10
EAI	324	4.90	3.14	0	10

Note. M = Mean; *SD* = Standard deviation; *Min* = Minimum; *Max* = Maximum; SRD = Support from the HR department; CFW = Real concern for workers; CAI = Comfort with AI; CIU = Concern for the interests of users; VAIH = Validity of AI to identify bullying situations; EAI = Ethics of the use of AI in HR.

Table 5
Descriptive statistics of participants' interlocutor preference for dealing with harassment.

	N	M	SD	Min	Max
PWP	326	6.66	2.99	0	10
PAI	326	3.75	3.29	0	10

Note. M = Mean; *SD* = Standard deviation; *Min* = Minimum; *Max* = Maximum; PWP = Prefers to tell people about harassment; PAI = Prefers to tell Artificial Intelligence systems about harassment.

4.2. Aspects that influence the preferences of the interlocutor to whom to narrate the situations of harassment

To determine this influence, a linear regression will be used that must meet the assumptions: *independence, normality, linearity, non-collinearity and homoscedasticity.*

Independence. The Durbin–Watson statistic (1951) provides information on the degree of independence among the residuals. The statistic ranges from 0 to 4 and takes the value of 2 when the residues are independent. Values less than 2 indicate positive autocorrelation and those greater than 2 indicate negative autocorrelation. Independence between residuals can be assumed when the Durbin–Watson statistic takes values between 1.5 and 2.5. In our case, the Durbin–Watson statistic takes a value of 1.835.

Table 6
Multiple regression analysis of the preference to have people or AI as an interlocutor.

	Model	Variables	R^2	$R^2_{ajusted}$	UC		SC	*t*	*p*	95%Conf. – B Interval
					B	SE	β			
H1	1	Constant	0.106	0.104	3.238	0.586		5.525	0.000	2.085 – 4.390
		MFW			0.469	0.076	0.326	6.176	0.000	0.320 – 0.619
	2	Constant	0.142	0.137	4.856	0.726		6.685	0.000	3.427 – 6.286
		MFW			0.417	0.076	0.290	5.484	0.000	0.267 – 0.566
		WOL			−0.193	0.053	−0.193	−3.646	0.000	(−0.297) – (−0.089)
	3	Constant	0.156	0.148	4.183	0.778		5.375	0.000	2.652 – 5.714
		MFW			0.318	0.087	0.221	3.674	0.000	0.148 – 0.489
		WOL			−0.177	0.053	−0.176	−3.333	0.001	(−0.281) – (−0.072)
		AKQ			0.174	0.075	0.140	2.309	0.022	0.026 – 0.323
H2	1	Constante	0.044	0.041	2.267	0.425		5.331	0.000	1.430 – 3.104
		WOL			0.234	0.061	0.210	3.845	0.000	0.114 – 0.354
H3	1	Constant	0.193	0.190	2.522	0.507		4.974	0.000	1.524 – 3.520
		CWE			0.586	0.067	0.439	8.701	0.000	0.453 – 0.718
	2	Constant	0.238	0.234	4.126	0.616		6.700	0.000	2.914 – 5.337
		CWE			0.446	0.073	0.334	6.114	0.000	0.302 – 0.589
		HPS			−0.235	0.054	−0.238	−4.351	0.000	(−0.342) – (−0.129)
H4	1	Constant	0.168	0.165	2.613	0.221		11.840	0.000	2.178 – 3.047
		AEPE			0.457	0.057	0.410	8.032	0.000	0.345 – 0.569
H5	1	Constant	0.213	0.210	4.110	0.313		13.133	0.000	3.495 – 4.726
		CFW			0.454	0.049	0.461	9.319	0.000	0.358 – 0.550
H6	1	Constant	0.435	0.434	0.023	0.276		0.084	0.933	(−0.521) – 0.567
		VAIH			0.775	0.050	0.660	15.634	0.000	0.677 – 0.872
	2	Constant	0.505	0.502	−0.456	0.269		−1.696	0.091	(−0.986) – 0.073
		VAIH			0.494	0.063	0.420	7.852	0.000	0.370 – 0.617
		EAI			0.372	0.056	0.356	6.648	0.000	0.262 – 0.483
	3	Constant	0.523	0.519	−0.720	0.275		−2.622	0.009	(−1.261) – (−0.180)
		VAIH			0.424	0.065	0.361	6.544	0.000	0.297 – 0.552
		EAI			0.302	0.059	0.289	5.160	0.000	0.187 – 0.417
		CAI			0.194	0.055	0.179	3.525	0.000	0.086 – 0.302

Note. UC = Unstandardized coefficients; SC = Standardized coefficients; MFW = Motivation for work; AKQ = Adequacy of qualification; WOL = Work overload; CWE = Work environment; HPS = Harassment of personal status; CFW = Real concern for workers; CAI = Comfort with AI; VAIH = Validity of AI to identify bullying situations; EAI = Ethics of the use of AI in HR.

Table 7
Summary of hypothesis compliance.

Hypothesis
H1: There is a positive relationship between workers with higher job satisfaction and a preference for dealing with bullying situations with others in the company.
H2: There is a positive relationship between workers with lower job satisfaction and a preference for dealing with bullying situations with AI systems.
H3: Working in friendly work environments is positively related to a preference for dealing with workplace bullying with people in the organisation.
H4: Working in hostile work environments is positively related to a preference for dealing with harassment at work with AI systems.
H5: Employees' trust in HR departments is positively related to their preference to deal with a situation of harassment at work with individuals.
H6: Workers' trust in AI systems influences their preference to deal with a situation of workplace harassment with robots.

Normality. Despite having a large sample that could allow the assumption of normality of the model, this assumption can be observed in the histogram. The histogram offers us the typified residuals with a superimposed normal curve. The curve is constructed by taking an average of 0 and a standard deviation of 1, i.e. the same mean and the same standard deviation as the typified residuals. Our data follow a normal distribution.

In the same way, the normal probability plot of the residuals allows comparison of the cumulative probability that corresponds to each typified residue with the theoretical cumulative probability that corresponds to each typical score on a normal curve with mean 0 and standard deviation 1.

When the residuals are normally distributed, the point cloud is aligned on the graph diagram, as is practically the case in our data.

Linealidad. Ha de existir una relación lineal entre la variable independiente y la variable dependiente. Se ha examinado este supuesto por medio del análisis de residuos y se cumple este supuesto (Martínez Arias, 2008).

Non-collinearity. This assumption refers to the fact that there should be no exact linear relationship between any of the independent variables.

When the tolerance values are very small, as is the case, they indicate that this variable can be explained by a linear combination of the rest of the variables. On the other hand, eigenvalues report on how many different dimensions or factors underlie the set of independent variables used. The presence of several eigenvalues used close to zero indicate that the independent variables are closely related to each other.

The variance inflation factor (VIF) and the tolerance (T) were used to measure collinearity. According to Kleinbaum, Kupper, Nizam, and Rosenberg (2013) and Newbold (1998), collinearity problems are considered to exist if any VIF is greater than 10 and the tolerance is less than 0.10, which is not the case in this study.

Homoscedasticity. For each value of the independent variable, the variance of the residuals is constant. For this, the behaviour of the standardised residual value for each of the observed values will be observed, whose scatter plot informs about the assumption of homoscedasticity or equality of variance. The assumption of equality of variances implies that the variation of the residuals must be uniform throughout the range of predicted values, from which it follows that the scatter plot must not show any pattern of association between the forecasts and the residuals, as is the case (Baños, Torrado-Fonseca, & Álvarez, 2019).

If the five assumptions to be met by the multiple linear regression model, independence, normality, linearity, collinearity and homoscedasticity, are analyzed together, it is observed that all of them are met. In this model, none of the separate assumptions is expected to be failed. Normally, if one is not satisfied, several of the others are not satisfied. Therefore, we assume that the assumptions of the model are fulfilled.

In the multiple linear regression analysis carried out for H1 (Table 6), with respect to the dimensions of professional satisfaction, motivation for work, work overload and the adequacy of the qualification to the demands of the job explain 14.8% of the variance of the preference to have people as interlocutors to talk to about harassment. Motivation is the dimension that produces the most important effect ($\beta = 0.221$), followed by the negative effect of overload ($\beta = -0.176$) and rating adequacy ($\beta = 0.140$).

In the case of the analysis for H2, it is shown that with respect to professional satisfaction, the model explains 4.1% of the variance of the preference to have AI as an interlocutor to count harassment, and that motivation is its only predictor ($\beta = 0.210$).

In the analysis of regression of the H3, it has been revealed that the problems in the work environment, the work environment of the company, and the harassment of personal status explain 23.4% of the variance of the preference to have as an interlocutor people to talk to about harassment. The work environment is the dimension that produces the most important effect ($\beta = 0.334$), followed by the negative effect produced by harassment of personal status ($\beta = -0.238$).

For H4, the analyses show that regarding the dimensions of the problems of the work environment, the model explains 16.5% of the variance of the preference to have AI as an interlocutor to talk about harassment, and that personal status harassment is its only predictor ($\beta = 0.410$).

In the analysis for H5, regarding the dimensions of trust in HR, the model explains 21% of the variance of the preference to have people as an interlocutor to talk to about harassment, and that the real concern of HR for the workers of the company is its only predictor ($\beta = 0.461$).

For H6, the results indicate that regarding trust in AI systems, the validity of AI to identify harassment, the ethical consideration of the use of AI for HR and comfort dealing with AI systems explain 51.9% of the variance of the preference to have robots as an interlocutor to talk to about harassment. The validity of AI in identifying harassment is the dimension that produces the most important effect ($\beta = 0.361$), followed by the effect of ethical use of AI on HR ($\beta = 0.289$) and comfort with AI ($\beta = 0.179$).

In summary, it can be stated that all the hypotheses put forward have been tested.

5. Discussion of results

The research confirms the six hypotheses raised regarding that when people have confidence in other people in the company or its HR departments, there is a preference for using this route to solve labour problems.

In the analysis of the correlations between the variables related to workplace harassment and the variables related to trust in HR and AI systems, it is reflected that the preference to have people as an interlocutor correlates positively with the concern of HR for workers and negatively with the validity of AI to identify harassment and the ethics of the use of AI in people management. On the other hand, the preference to choose AI as an interlocutor correlates positively with the validity of AI to identify harassment, the ethical consideration of AI in HR and negatively correlates with concern for workers and department support confirming the initial theoretical model developed in this research. This result corresponds to those obtained by Malik, Sinha, and Goel (2022) in a study conducted in 563 surveys found it likely that social networks are used as a resource by victims of sexual harassment at work to cope with this situation which gives a measure of the possibilities that technology gives as a solution to problems of harassment at work.

The results in Table 5 reveal a lack of trust in AI to address cases of workplace harassment, three points lower than dealing with humans, a reality that leads us to the need for greater awareness of the possibilities of AI beyond the automation of processes. According to Braganza, Chen, Canhoto, and Sap (2021) in a study on the effects of AI adoption on psychological contract, commitment and trust of workers in a sample of 232 surveys, they concluded that psychological contracts had a positive and significant effect on work commitment and trust, however, with the adoption of AI, the positive effect of psychological contracts was significantly reduced. The focus should be on informing the worker about the possibilities offered by this technology with regard to emotional management in the work environment.

AI poses ethical dilemmas about privacy that may be based on the theory of social identity (Tajfel & John, 1979), which defines an individual who needs to be identified in an environment of equals, where they can share and develop an individuality sponsored by the recognition of the group in which it is integrated (Stets & Burke, 2000). For Turner et al. (1987), the theory has three main components: social categorisation, social identification and social comparison, three aspects with which AI, applied to Human Resources management, in a subject as delicate as *mobbing*, must still advance. However, the road ahead does not seem so long if we take into account the results presented in Table 4, where there is not a great difference in the perception of workers between the concern that HR and AI have for people.

In a study of organizational citizenship behavior (OCB), its antecedents (interactional justice and affective commitment) and the circumstances that can exacerbate or weaken these relationships, López-Cabarcos, Vazquez-Rodriguez, Pineiro-Chousa, and Caby (2020) found in the sample analyzed that bullying at work weakens the relationship between interactional justice and affective commitment. This article contributes to identify that OCB is affected by different factors as is the case of workplace bullying, generating difficulties of interaction and trust within the company. Managers should try to promote affective relationships between the organization and employees and protect these relationships to ensure an environment of trust among workers and also with the management team. When the opposite happens, that is, more confidence in AI, the hypotheses related to seeking help preferentially in AI systems are fulfilled. This is related because AI systems have the possibility of processing huge amounts of data very quickly, and with a high capacity to find the cause-effect relationships of the analysed data and to make decisions automatically. In recent years, with the incursion of AI in the different activities of the company, there are many AI systems that try to identify emotions such as anger, contempt, disgust, fear, happiness, neutrality, sadness, and surprise through gestures. For example, Microsoft's Emotion API claims to be able to detect what a person feels only from images of their face (Barrett, Adolphs, Marsella, Martinez, & Pollak, 2019). Even in the field of medicine, gestures and tone of voice help diagnose diseases such as autism (Golan, Baron-Cohen, Hill, & Rutherford, 2007). But this, which is an absolute truth for many, is questioned by other authors such as Keltner and Cordaro (2017), who defend that there is no exact correspondence between facial gestures and vocal signals and each and every one of the emotions.

In the business world, demotivation and burnout at work are widely studied phenomena because of the impact they have on people and the functioning of organisations. The relationships between burnout and different factors have been studied, such as: job satisfaction (Chen & Scannapieco, 2010); retention (O'Donnell & Kirkner, 2009); and work environment (Perrone, 2007). This has caused the interest of researchers to focus not only on how to solve it, but also how to predict it. For *burnout* predictions, statistical models have been used, mainly logistic regression, in which the volumes of data analysed are very limited

(Søbjerg et al., 2020). Oosthuizen (2019) stated that the introduction of AI in companies can have an effect on the well-being of employees, who, as indicated by Seal (2019) are already familiar with the use of AI, since 67% of users and consumers are using in one way or another, consciously or not, technologies related to AI such as interactive *chatbots* and smart clothing, personal digital assistants in the home among others.

As in this research, Bethel et al. (2016) found that in the case of bullying, there is evidence that compares the results when children are interviewed by a human versus cases in which children are evaluated by a robot like a human, a humanoid. Robots were found to be more effective at obtaining concrete details about harassment.

There are many researchers who have considered the impact that new technologies, such as AI, can have on employees in organisations, both because of the fear that their jobs will be replaced by machines and because of the lack of confidence in them (McClure, 2018) or the ethical dilemma involved (Aalberts, Hames, & Thistle, 2009, & Yam, Tang, Jackson, Su, & Gray, 2022). Along the same lines, Yam et al. (2022) state that employees who have a lot of relationships with robots in their workplace feel greater job insecurity, precisely because they perceive that they can easily be replaced. Others have tried to study whether a robot can be a good colleague, one of the most valued aspects when perceiving a good working environment (Nyholm & Smids, 2020).

6. Conclusions

In the business world, demotivation and burnout at work are widely studied phenomena because of the impact they have on people and the functioning of organisations. The relationships between burnout and different factors have been studied, such as: job satisfaction (Chen & Scannapieco, 2010); retention (O'Donnell & Kirkner, 2009); and work environment (Perrone, 2007). This has caused the interest of researchers to focus not only on how to solve it, but also how to predict it. For *burnout* predictions, statistical models have been used, mainly logistic regression, in which the volumes of data analysed are very limited (Søbjerg et al., 2020). Oosthuizen (2019) stated that the introduction of AI in companies can have an effect on the well-being of employees, who, as indicated by Seal (2019) are already familiar with the use of AI, since 67% of users and consumers are using in one way or another, consciously or not, technologies related to AI such as interactive *chatbots* and smart clothing, personal digital assistants in the home among others.

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6.1. Limitations of the study

In terms of the limitations of the study, the first is users' concerns about privacy, fairness and justice. The positive points of the application of AI to companies are that they could improve the efficiency, fairness and safety of workers. However, these systems raise some ethical issues. McKinsey (2021), in a survey on the situation of AI at work, found that 44% of respondents in advanced economies expressed concern about their explainability, or, which amounts to the same thing, the ability that the results of the solution can be understood by expert humans; 41% were concerned about privacy, and 30% about the fairness and justice they are able to manage. The second limitation is the ethical dilemma of the fulfilled prophecy or the Pygmalion effect, in relation to managers' perceptions of workers. AI predicts expected behaviours, such as poor worker performance. What will happen if a manager receives this information? Will this expectation project onto the worker? Will this projection influence the performance of that worker? All this initial analysis conditions how to apply AI to the different functions of people management. Regardless of the stage of development that is being applied in AI, the data generated and past behaviours always condition future behaviors in some way. That is, if the management systems are correct and productive, they will be reflected in future behaviours, but if they are not, there is also a strong possibility that they will be replicated and continue to be institutionalised in the future. Therefore, AI systems should be as open as possible and avoid the inbreeding of working inwards in the company.

6.2. Future lines of research

Finally, about future lines of research, this research constitutes an exploratory study, since, to date, there is no similar analysis on this combination of variables, and research should continue in the future, expanding the sample size, contrasting if the results are similar in other countries. In the future, and knowing that the hypotheses have been contrasted, it is proposed to carry out a broader questionnaire where validated scales are studied for each variable. This research considers all workers as a population. It is not an investigation stratified by sectors so it is not intended to draw differentiated conclusions by sectors and therefore a representativeness of these has not been sought. In the future, it would be interesting to know whether workers from all sectors behave in the same way. This research also opens the door to different ethical dilemmas, such as information protection and the level of exposure of individuals several studies have addressed the importance of balancing cyber surveillance policies that effectively serve risk management objectives of employers without unduly invading the privacy of employees, and the likely consequences of failing to achieve that balance, a phenomenon that is even more sensitive in issues related to workplace bullying.

CRediT authorship contribution statement

María de las Mercedes De Obesso Arias: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Investigation, Methodology, Supervision. **Carlos Alberto Pérez Rivero:** Conceptualization, Data curation, Writing – original draft, Investigation, Methodology. **Oliver Carrero Márquez:** Conceptualization, Writing – original draft, Writing – review.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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