Received: 25 April 2023 | Revised: 26 April 2024 | Accepted: 20 June 2024
DOI: 10.1111/exsy.13673

REVIEW

Expert Systems WILEY

The study of engagement at work from the artificial intelligence perspective: A systematic review

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Abstract

Engagement has been defined as an attitude toward work, as a positive, satisfying, work-related state of mind characterized by high levels of vigour, dedication, and absorption. Both its definition and its assessment have been controversial; however, new methods for its assessment, including artificial intelligence (AI), have been introduced in recent years. Therefore, this research aims to determine the state of the art of AI in the study of engagement. To this end, we conducted a systematic review in accordance with PRISMA to analyse the publications to date on the use of AI for the analysis of engagement. The search, carried out in six databases, was filtered, and 15 papers were finally analysed. The results show that AI has been used mainly to assess and predict engagement levels, as well as to understand the relationships between engagement and other variables. The most commonly used AI techniques are machine learning (ML) and natural language processing (NLP), and all publications use structured and unstructured data, mainly from self-report instruments, social networks, and datasets. The accuracy of the models varies from 22% to 87%, and its main benefit has been to help both managers and HR staff understand employee engagement, although it has also contributed to research. Most of the articles have been published since 2015, and the geography has been global, with publications predominantly in India and the US. In conclusion, this study highlights the state of the art in AI for the study of engagement and concludes that the number of publications is increasing, indicating that this is possibly a new field or area of research in which important advances can be made in the study of engagement through new and novel techniques.

KEYWORDS
artificial intelligence, engagement, machine learning, natural language processing

1 | INTRODUCTION

In recent years, researchers have shown interest in using machine learning (ML) algorithms to analyse structured and unstructured engagement data to extract valuable information from this type of data (van Zoonen & van der Meer, 2016). Structured data refer to quantitative data following a predefined model, with limited formats and, as a general rule, easy to analyse (e.g., item scores of self-report instruments), while unstructured data refer to qualitative data, not following a particular schema and with a wide variety of formats (e.g., text from social networks, comments to open-ended questions in self-report instruments, text from corporate tools, and blogs).

After the implementation of the use of artificial intelligence (AI) in the study of psychological variables such as personality traits, anxiety and depression, among others (Eichstaedt & Weidman, 2020; Loveys et al., 2017), in the area of work and organizational psychology, ML and natural language processing (NLP) algorithms began to be used to study other variables such as burnout, job satisfaction and engagement (Chug & Vibhuti, 2017; Knijnenburg & Willemsen, 2015; Speer et al., 2022). This research aimed to improve engagement assessment using AI versus self-report measures. The use of self-report measures presents numerous limitations related to the frequency of administration, credibility, representativeness or reliability, among others (Bernardi & Nash, 2022; Krumpal, 2013; Shami et al., 2015). Although this form of measurement remains a popular choice for engagement assessment, alternative methods such as ML and NLP are gaining considerable importance (Speer et al., 2022).

Currently, an increasing number of studies are applying ML and deep learning (DL) models to the fields of personality (Dai & Wang, 2023), work and organizational psychology (Kwon et al., 2021) and clinical practice (Senn et al., 2022). In recent years, there has been an exponential increase in the application of these ML models to the study of engagement. The reason for this growth is that AI techniques can easily extract information from structured and unstructured data and analyse its content in a short period of time, whereas traditional techniques have some of the limitations mentioned above.

All the systematic reviews or meta-analyses regarding the study of engagement that have been performed thus far have collected both the background and the current state of academic research on this variable (Knight et al., 2017; Mazzetti et al., 2021; Shuck, 2011); however, there is no single study that reviews the introduction of AI in the study of engagement. To propose tools and techniques that allow the assessment of engagement in the future, without the limitations that self-report measures have thus far, we need to know what is the state of the art in the application of AI to the study of engagement.

This research provides a valuable contribution by establishing where the use of AI in the study of engagement stands and describing what specific AI techniques have been used thus far to understand their advantages over the use of more traditional measures such as self-reporting.

It is important to address this problem since it is not known with certainty whether these techniques overcome the limitations of self-report instruments, the extent of their effectiveness or whether they provide additional benefits in the study of engagement. Therefore, knowing whether the AI techniques that have been used for the study of engagement are truly effective or whether these instruments also have limitations opens up avenues for the improvement of AI instruments in the future, giving rise to new lines of research that will develop more accurate and up-to-date instruments for studying engagement.

Knowing about these advances, a new way of studying engagement can provide companies with a new technique and/or tool that avoids all the limitations of self-reporting instruments. This will ultimately allow companies to know in a more reliable way and with more advantages than limitations on the level of employee engagement. Therefore, this study has the following important implications:

- Research advance: This study represents a significant advance in research on work engagement from an AI perspective. As the first systematic review in this field, this study contributes to consolidating existing knowledge and identifying areas of opportunity for future research.
- Contribution to the literature: By compiling and analysing the literature on the use of AI in the study of work engagement, this paper contributes to enriching the body of knowledge in this emerging field. Furthermore, this study highlights the relevance of ML and NLP techniques in understanding key aspects of employee engagement.
- Practical applications in industry: Provides a sharp focus on new trends in business that can help organizations understand which techniques are best suited to assessing engagement. By measuring engagement effectively, organizations can create healthier, more productive and motivating work environments, which in turn can contribute to the long-term success of the company.

Therefore, this work is important for its contribution to the advancement of research in the field of work engagement, its practical applications in the business domain and its contribution to the academic literature on the intersection between AI and employee engagement.

The main objectives of this review paper are (i) to compile the relevant studies prevailing in the field of AI related to the use of ML and NLP models for the prediction of engagement levels, the methods applied and the results obtained; (ii) to determine the state of the art of ML and NLP models in relation to the study of engagement; and (iii) to identify opportunities and future lines of research toward different approaches for the prediction of engagement.

This review article is structured as follows: Section 2 presents the theoretical background of employee engagement (Section 2.1) and the limitations of the literature (Section 2.2) the emergence of AI in employee engagement (Section 2.3) and the research and motivation gap (hypotheses or research questions, Section 2.4). Section 3 presents the methodology by which the systematic review of all related and identified papers is carried out. Section 4 presents the results, which are divided into general questions, specific questions and statistics. The discussion, which includes limitations and future lines of research, and the conclusions drawn from the various existing investigations are included in Section 5. Finally, last section presents the references. All sections are shown in Figure 1.

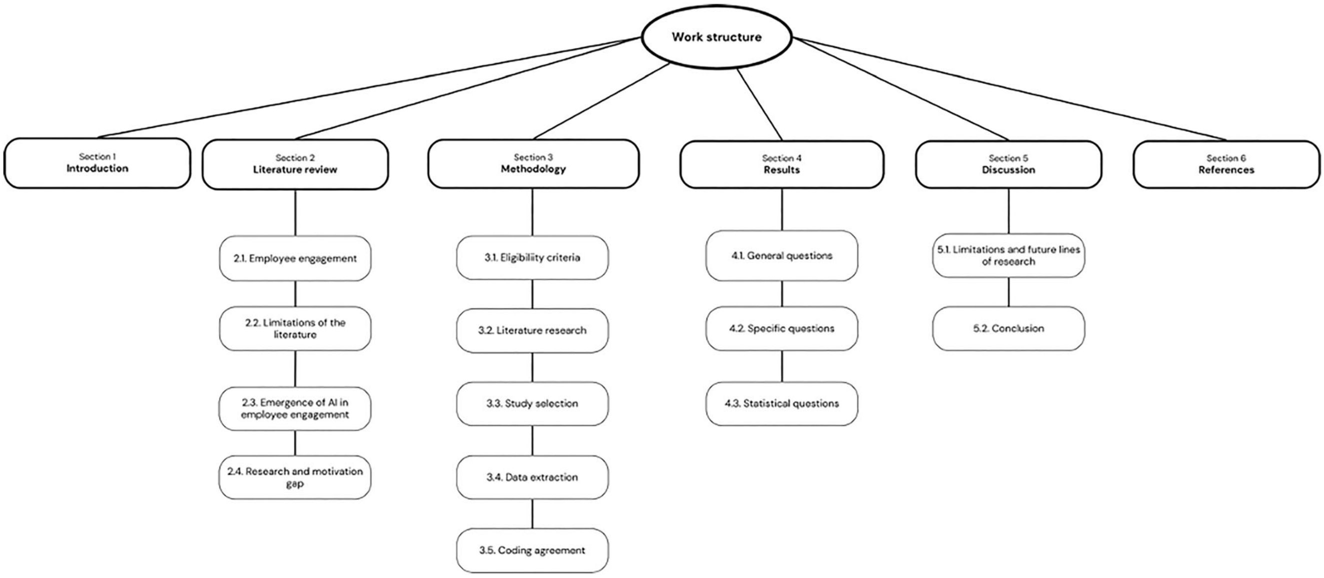

FIGURE 1 Work structure.

2 | LITERATURE REVIEW

2.1 | Employee engagement

The concept of engagement has been associated with a number of positive consequences for organizations, such as talent management and retention, which ultimately contributes to improved financial performance (Chandni & Rahman, 2020). It increases productivity (Hughes & Rog, 2008), protects against burnout (Hakanen et al., 2018) and the intention to leave the organization (Saks, 2006), and enables cost savings (Chug & Vibhuti, 2017). The concept explains variance in external turnover levels beyond that explained by, among others, performance (Hakanen et al., 2018), thus gaining much attention among academics and practitioners (Barnes et al., 2014). The current paradigm in which we find ourselves with changing market dynamics, technological advances, fierce competition and unprecedented levels of customer interaction makes it necessary for organizations to be aware of how employee engagement can help them achieve greater competitive advantage (Pansari & Kumar, 2017). Engagement is intrinsically beneficial to organizations, and its lack is a problem that needs to be addressed (Afrahi et al., 2021).

The consulting firm Gallup estimates the cost to the economy of lost productivity due to workers leaving a company because of low levels of engagement at $605 billion. However, only 13% of employees worldwide report experiencing engagement at work (Oxford Economics, 2020). In Europe, the Netherlands (18.5%) and Belgium (17.6%) have the highest percentages of workers experiencing engagement, while at the opposite end of the scale are Germany (4.3%) and Sweden (6.4%) (Schaufeli, 2018). The variables that contribute most to engagement are occupational group and sector of activity (Hakanen et al., 2018). This explains why the most economically developed countries (in terms of economic activity and productivity) have the highest number of workers who experience engagement. Taking these figures into account, a 10% increase in investment in employee engagement could increase profits by USD 2400 per employee per year (Quiambao, 2020), as companies with engaged employees perform better than those without engaged employees.

Investing in engagement will therefore lead to a higher level of employee engagement, lower absenteeism rates and lower intentions to leave the organization (Bakker & Schaufeli, 2008), in turn increasing well-being and performance (Lin, 2007) at both the individual and organizational levels (Vîrgă et al., 2021). This is due to the relationship between engagement and motivational processes. When workers show high levels of engagement and motivation, they feel driven to achieve challenging goals to succeed at work (Leiter & Bakker, 2010), which is associated with higher customer service quality, customer loyalty and satisfaction (Salanova et al., 2005) and financial performance (Xanthopoulou et al., 2009). In addition to these benefits, employees experience positive emotions and high job satisfaction (Jeanson & Michinov, 2020), enjoy good physical and mental health, show personal initiative and innovative behaviour (Jason & Geetha, 2021) and are strongly eager to learn (Han et al., 2021), which positively impacts their work (Demerouti et al., 2001).

Engagement has been widely studied from different approaches and perspectives (Bakker & Demerouti, 2008; Shuck et al., 2017), both at the theoretical level and in terms of its assessment (see Table 1).

Kahn's initial proposal, based on ethnographic work, defines engagement as the harnessing of organization members' selves to their work roles, by which they employ and express themselves physically, emotionally, and cognitively during their role (Kahn, 1990). From this same perspective, several studies have proposed changes to it or the inclusion of complementary aspects. Thus, aspects such as attention devoted to and

TABLE 1 Approaches in the study of engagement.

Engagement definitions		
Original proposal	Derivations or adaptations	Measuring instrument
Kahn (1990)	Rothbard (2001) Shirom (2004) Saks (2006)	*Work Engagement Survey* (Rothbard, 2001) *Shirom-Melamed Vigour Measure* (SMVM; Shirom, 2004) *Engagement Scale* (May et al., 2004) *Job and Organization Engagement Scales* (Saks, 2006) *Employee Engagement Scale* (EES; Kamalanabhan et al., 2009) *Job Engagement Scale* (Rich et al., 2010) *JRA Employee Engagement Scale* (JRA, 2007)
Maslach and Leiter (1997)	Schaufeli et al. (2002)	*Maslach Burnout Inventory* (MBI; Maslach & Jackson, 1981) *Utrecht Work Engagement Scale* (UWES; Schaufeli et al., 2002)
Britt (1999)		*Soldier Engagement* (Britt, 1999)
Harter et al. (2002)		*The Gallup Workplace Audit* (GWA; The Gallup Organization, 1992–1999)
Macey and Schneider (2008)		*Engagement Survey* (Macey et al., 2009) *Engagement Survey* (Stumpf et al., 2013)
Soane et al. (2012)		*ISA Engagement Scale* (Soane et al., 2012)

absorption in work have been highlighted (Rothbard, 2001). Attention refers to the time spent concentrating on and/or thinking about the activity performed, while absorption refers to the intensity of concentration and is reflected in the loss of the notion of time when performing the activity. Shirom (2004) also highlights the physical, emotional and cognitive components of the concept, considering it a positive affective reaction to persistent interactions with significant aspects of one's work and work environment comprising the interconnected feelings of physical strength, emotional energy and cognitive vitality. The same components are highlighted in the proposal by Saks (2006), who argues that engagement reflects the extent to which an employee is psychologically present in a particular organizational role. This makes it possible that, in view of these differentiated roles, we can talk about work role (job engagement) and the role as a member of an organization (organization engagement).

On a different theoretical basis, Maslach and Leiter (1997) define engagement as the antithesis of burnout. The positive pole of the dimensions of burnout (exhaustion, cynicism, and reduced personal efficacy) reflects the components of engagement (high energy, strong involvement and a sense of efficacy). The authors define engagement as an enduring positive affective state marked by high levels of activation and satisfaction (Maslach & Leiter, 1997). Since Maslach and Leiter's contribution, Schaufeli et al. (2002), who accepted a bivariate view of positive and negative emotions, have introduced variations in the definition of engagement by considering it a positive and rewarding emotional state linked to the work environment, satisfactory and work-related, characterized by vigour, dedication and absorption. Vigour implies high levels of energy and mental stamina while working; dedication refers to being strongly involved in one's work and experiencing a sense of importance, enthusiasm and challenge; and absorption refers to being totally focused and absorbed in one's work (Bakker & Demerouti, 2007).

A combination of responsibility and commitment is what Britt (1999) understands as engagement. An engaged employee experiences a sense of personal responsibility for his or her performance that influences his or her identity (Britt et al., 2007). In contrast to other proposals, Britt considers engagement a unidimensional concept that represents a motivational state generated by personal beliefs of responsibility and caring. Britt (1999) posits vigour, effort, attention and absorption more as consequences of the concept than as components of it.

According to Harter et al. (2002), an individual's involvement and satisfaction with and enthusiasm for work are the basis of engagement. These authors state that engagement develops when employees connect with other people in their work contexts and when they are cognitively vigilant. This only occurs when they have at their disposal what they need to work, know their role expectations, have the opportunity to feel fulfilled in their work, feel part of something important together with their colleagues and can improve and develop professionally (Harter et al., 2002).

In an attempt to propose a taxonomy that encompasses different conceptual approaches to engagement, Macey and Schneider (2008) suggest that engagement is a desirable condition with an organizational purpose that connotes involvement, passion, enthusiasm and energy. According to these authors, engagement has attitudinal and behavioural components and is divided into three types that affect each other: trait engagement, state engagement and behavioural engagement. From this perspective, engagement consists of intentional initiatives aimed at going beyond the strict demands of the job.

Finally, Soane et al. (2012) propose a new view of engagement based on activation, positive affect and focus. Activation refers to cognitive activity related to the roles performed at work, positive affect refers to consciously accessible feelings with a positive valence, and focus refers to the specific role performed.

With regard to the assessment of the concept, Table 1 also lists the instruments used in the assessment of engagement, connected to the different perspectives or approaches. The most widely used and widespread instrument (Christian et al., 2011; Halbesleben, 2010; Knight et al., 2017; Knight et al., 2019; Maricuţoiu et al., 2016; Shuck, 2011) is the Utrecht Work Engagement Scale (UWES; Schaufeli et al., 2002). It is available in 21 languages, and an international database currently includes engagement records of more than 60,000 employees. The UWES items are scored on a 7-point frequency scale ranging from 0 ('never') to 6 ('always'). In a sample of employees, internal consistency values were adequate for items in the three subscales (alpha values of .79, .89 and .72 for vigour, dedication and absorption, respectively; Schaufeli et al., 2002). Although there are papers that support the original theoretical factor structure (Bakker & Demerouti, 2008), the empirical evidence related to concept validity is not without controversy (for a review, see Byrne et al., 2016; Kulikowski, 2017; Mills et al., 2012; Seppälä et al., 2009; or Wefald et al., 2012; among others). Authors such as Mills et al. (2012) question the development of the scale itself by pointing out that the vigour dimension contains content related to perseverance.

The self-reported measures of engagement listed in Table 1 show wide variation in their psychometric properties. The *Engagement Scale* (May et al., 2004) has adequate internal consistency ($\alpha = .77$). However, most of them have good reliability, with α values equal to or greater than .80; these include the *Employee Engagement Scale* ($\alpha = .80$; Kamalanabhan et al., 2009), *JRA Employee Engagement Scale* ($\alpha = .85$; JRA, 2007), *Work Engagement Survey* ($\alpha = .87$; Rothbard, 2001), *ISA Engagement Scale* ($\alpha = .88$; Soane et al., 2012) and *Engagement Survey* ($\alpha = .89$; Stumpf et al., 2013). Those that achieved the highest internal consistency were the *Job and Organization Engagement Scales* (Saks, 2006), for which the α of the *Organizational Engagement Scale* was .90; the *Soldier Engagement Scale* (Britt, 1999); and the *Global Job Engagement Scale*, which was also reliable from the point of view of internal consistency ($\alpha = .95$). In the case of the *Shirom-Melamed Vigour Measure* (SMVM), the subscale of cognitive liveliness has an optimal internal consistency ($\alpha = .72$), while the subscales of physical strength and emotional energy have high internal consistency ($\alpha = .95$ and .88, respectively). For the Maslach Burnout Inventory (MBI; Maslach & Jackson, 1981), the internal consistency was very low for some of the subscales, such as involvement ($\alpha < .60$); adequate for others, such as personal fulfilment ($\alpha = .74$) and depersonalization ($\alpha = .77$); and high in the case of emotional exhaustion ($\alpha = .89$). For the Gallup measure, no copyright data were found, and no psychometric properties of the *Engagement Survey* were found (Macey et al., 2009).

The set of measures analysed also has the drawbacks of self-report measures. Although an increasing number of solutions to this problem are being proposed (Jordan & Troth, 2020), common method bias (Podsakoff et al., 2003) is still a drawback when self-report measures are used as the only method to assess concepts. Moreover, in many cases, conclusions about causal relationships between concepts are drawn when all self-reports are applied at the same point in time. If there is no possibility to differentiate between temporal moments (antecedents and consequents), it is very difficult to talk about causal relationships (Garrad & Patrick, 2020). In many cases, and this is also true for the assessment of engagement, self-report measures ask respondents to make reflective evaluations retrospectively, that is, by thinking about past work experiences. If such evaluations do not appropriately reflect current experiences in performing the job role, they are unlikely to allow for a valid assessment of the engagement experienced (Kahneman & Riis, 2005). Relatedly, self-report measures are often administered annually, which can prevent an organization from knowing or responding to emerging issues experienced by employees in real time due to large time lags in administration (De Choudhury et al., 2013). To address this problem, it has been proposed to administer self-report instruments on a more frequent basis, for example, quarterly (Saha et al., 2021). However, this has reduced employee interest in the instrument and increased the cost of time and resources due to repeated administration (Baruch & Holtom, 2008). To address this issue, self-report instruments in abbreviated versions have been proposed (Santalla-Banderali & Alvarado, 2022) for daily administration to save time and costs due to their quick administration. Although it is true that this type of shorter and faster administration has provided better results (Schaufeli et al., 2019), participants know what they are answering, as the questions they present are directed and biased; therefore, they may choose an answer that does not fully provide the truth about the item being asked due to social desirability (Bernardi & Nash, 2022; Krumpal, 2013), which affects the credibility of the results.

2.2 | Limitations of the literature

Engagement research has generated a wide range of studies that have contributed significantly to our understanding of this phenomenon. However, when critically examining these studies, several common limitations can be identified that require consideration. First, many of the studies reviewed are based on cross-sectional designs (Britt, 1999; Harter et al., 2002; Saks, 2006; Soane et al., 2012), which limits their ability to establish causal relationships between variables and to understand how engagement may change over time (Schaufeli et al., 2002). Furthermore, the generalizability of the results is also a limitation, as many of the studies have focused on specific samples or particular organizational contexts, making it difficult to extrapolate findings to other populations or work settings (Macey & Schneider, 2008; Maslach & Leiter, 1997; Shirom, 2004; Soane et al., 2012). Another limitation is the lack of consideration of contextual factors, such as organizational culture or leadership, which may influence employees' experience of engagement (Harter et al., 2002). These limitations underline the need for a comprehensive and contextualized approach to engagement research, considering both individual and organizational factors, as well as the diversity of work contexts in which these phenomena occur. The most common limitation among all studies, however, is related to credibility, as data collection relies heavily on employee responses, which may introduce response biases and affect the validity of the results (Bakker & Demerouti, 2007; Kahn, 1990).

Engagement has commonly been assessed with self-report instruments, which are also not free of limitations, both those inherent to self-report instruments in general (frequency of administration, representativeness or reliability, among others, Saha et al., 2021) and those inherent to engagement instruments in particular. The self-report instruments used to assess engagement have several limitations, such as low use, as most of them have been studied only once, so further research is needed to gain a greater level of knowledge and to develop and improve them (May et al., 2004; Xu & Thomas, 2011). In addition, their use is generally limited due to their applicability in more general work settings (Britt et al., 2001), and their availability and application in academic research are restricted (Harter et al., 2002). The psychometric properties also have limitations, as there is insufficient research to support its validity and reliability (Macey & Schneider, 2008), and in general, the psychometric properties of the instrument have limitations, especially related to construct validity (Byrne et al., 2016).

2.3 | Emergence of AI in employee engagement

With the problems outlined above, it is a mistake to assume that the use of self-report measures is the only effective way to investigate concepts in work settings. The use of alternative methodologies aided by technological advances in AI (e.g., computer-assisted text analysis and NLP) may allow for an enriching approach to the study of certain concepts in work settings (Garrad & Patrick, 2020). Indeed, the consideration of employee engagement in the 'new world of data' is considered to establish some avenues for future research (Fink & Macey, 2021). Language offers a window into the study of perception, cognition and other psychological processes and thus provides a useful perspective through which we can understand, quantify and eventually improve the contribution to the evaluation of psychological concepts (Loveys et al., 2017). Language is important because it is a particularly attractive and rich source of data for digital phenotyping (Fronzetti et al., 2021). Thus, increasing research is using the language provided in social network data to advance, for example, the understanding of well-being (Greco & Polli, 2020). In the face of the difficulties associated with employing surveys and self-information measures, data extracted from corporate tools and social networks provide a means to study longitudinal and real-time data (Yu et al., 2017). However, collecting these data is a challenging task, as a large volume of unstructured data makes it difficult to analyse and process. Big data are used to collect and analyse qualitative or unstructured data (social networks, corporate digital platforms, etc.). However, for these data to be processed correctly, it is necessary to apply nontraditional data processing techniques that allow the study and analysis of language, that is, AI (Sancho Escrivá et al., 2020). Therefore, we can conclude that, thus far, based on the aforementioned studies, the two AI techniques that have most studied and analysed language have been ML and NLP.

In relation to communication, one of the main applications of AI in psychology is NLP. This AI technology can be used to understand, interpret and manipulate human language. According to Rong et al. (2020), after collecting data for language analysis, NLP techniques are based on the application of AI through ML. ML is the study of computer algorithms that automatically improve through experience (Landers et al., 2019). This means that it is possible to make predictions or approximations based on information with similar characteristics. ML has the ability to recognize complex patterns by analysing large amounts of data from different sources, including smartphones and wearable devices (McHugh & Large, 2020). This technology has contributed to advances in different scientific areas, such as biology, physics and psychology (Heckler et al., 2022).

According to Speer and Delacruz (2021), an increasing number of studies are emerging on the use of AI to analyse language and thus deepen our understanding of different psychological concepts (Abd Rahman et al., 2018; Eichstaedt & Weidman, 2020). This research has been more numerous in the area of mental health or in the study of differential personality psychology (e.g., O'Dea et al., 2021; Tsugawa et al., 2015), although there are also examples of work related to work environments such as those aimed at understanding the level of employee satisfaction or job turnover rates (Murray & Lai, 2018; Ramamurthy et al., 2015). Engagement can also be analysed through communication (Karanges et al., 2015), which encompasses both the language people use to communicate and the interactions and relationships they maintain. In most organizations today, a large part of communication between employees and with customers occurs through digital platforms (Misuraca et al., 2020), such as email, intranets, and online forums, where employees can interact and exchange opinions and ideas (Jarvenpaa & Leidner, 1999). It has been shown that the use of digital communication helps in understanding the level of employee engagement, as these tools allow employees to have more direct contact with managers and therefore feel more involved in organizations, which has an impact on future business performance (Detert & Burris, 2007). For this reason, among others, organizations are starting to make use of public communication channels, such as Twitter. Tools are being developed to monitor conversation channels and determine people's engagement levels. Indeed, the use of social media (e.g., Facebook, Twitter, and Yammer) in companies has been shown to influence information sharing (Brzozowski, 2009; Ehrlich & Shami, 2010).

The importance of applying AI techniques to understand the level of engagement that employees have in their companies can help companies to know how employees are doing so that they do not have to go through a laborious and time-consuming process of administering, correcting and interpreting surveys or self-report measures (Lilienthal, 2002). In addition, knowledge of the level of engagement can provide insight into turnover intentions since before turnover occurs, employee engagement levels are low. The cost of turnover for companies is very high, so using this type of tool can be beneficial for both parties. The few studies using AI techniques to analyse engagement levels have shown promising results (Zhu et al., 2020).

2.4 | Research gap and motivation

Research on the use of AI techniques to understand engagement has not received as much attention as other aspects of psychology related to personality or mental health. To date, there is no review of the scientific literature that compiles what is known about the use of AI in the study of engagement. Therefore, this is the first study that systematically reviews the research that has been conducted thus far on the use of AI to process and analyse engagement through free text data extracted from various information sources. To answer the question 'what is the state of the art of AI in the study of engagement?' a review of studies in which AI techniques were used for the study of engagement was conducted. The questions that the study aimed to answer are presented in Table 2.

3 | METHODOLOGY

This systematic review aimed to analyse all articles published on the use of AI to study engagement concepts. The present review was structured on the basis of the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) criteria (Page et al., 2021).

3.1 | Eligibility criteria

Full-text articles and conference contributions published in English and Spanish up to 2023 were included in this review.

Articles with formats such as letters to the editor, book chapters, books, opinion articles and short commentaries were excluded.

3.2 | Literature research

The first review period ran from when publications were available until December 2021. To update the article, the second review period ran from January 2022 to December 2023. The databases selected for the research were the APA PsycArticles, Web of Science, Scopus, Proquest Psychology Database, Association for Computing Machinery (ACM) and Institute of Electrical and Electronic Engineers (IEEE), and the Google Scholar database was searched for grey literature. The relevance of these databases is attributed to the inclusion of various academic journals related to psychological issues or technological aspects, specifically AI.

TABLE 2 Research questions.

Type of question	Question
General	What are the objectives of research using AI to study engagement?
Specific	What were the sources of the data used to feed the AI models?
Specific	What AI techniques have been used to study engagement?
Specific	How has the use of AI benefited the study of engagement?
Specific	What model accuracy has been achieved in the different studies?
Statistics	In which geographical regions is the research carried out?
Statistics	How many articles are published per year?

TABLE 3 Total results according to the search terms in each database.

Database	Search terms 1	Search terms 2	Results
Web of Science	19	25	44
Psychology Database	101	125	226
IEEE	23	19	42
ACM	39	36	75
Scopus	23	63	86
PsycARTICLES	18	14	32
Google Scholar	–	–	9

The search terms were divided into two large blocks. The first block contained the following search terms: ('work engagement' OR 'job engagement 'OR 'employee engagement') AND ('employee' OR 'worker') AND ('natural language processing' OR 'NLP' OR 'text mining' OR 'sentiment analysis' OR 'text classification' OR 'document classification' OR 'machine learning' OR 'supervised machine learning' OR 'unsupervised machine learning'). The words contained in the second block were ('work engagement' OR 'job engagement' OR 'employee engagement') AND ('employee' OR 'worker') AND ('artificial intelligence'). The second search term included AI because this concept includes other concepts, such as voice, robotics and DL, which are not found in the previous concepts. Table 3 illustrates the full search strategy implemented and the results generated from each of the six databases utilized.

3.3 | Study selection

Figure 2 summarizes the methodology and shows the steps followed to obtain the final number of articles. During the identification phase, 505 relevant papers were identified for the search terms; in addition, 9 articles were found in the Google Scholar database, and a total of

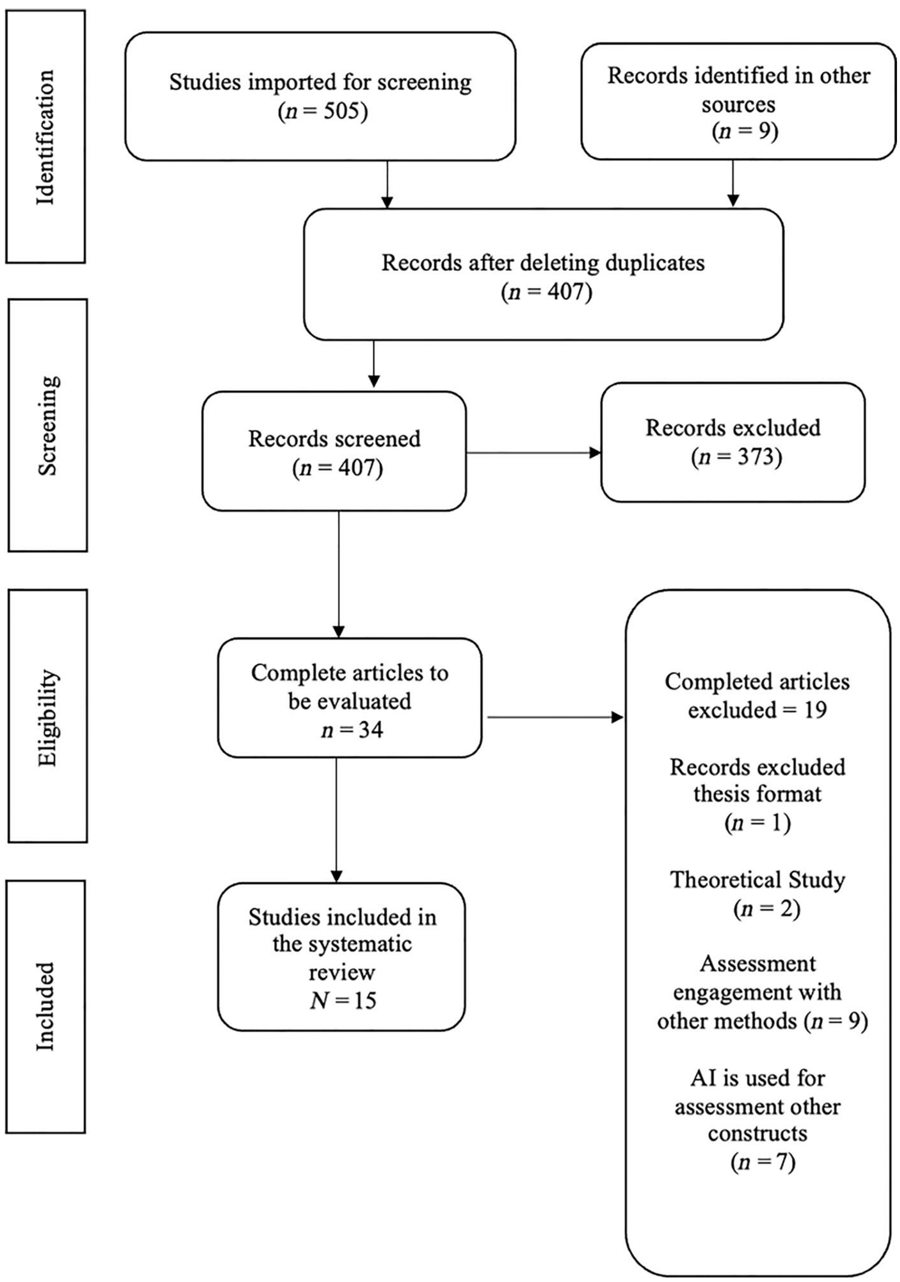

FIGURE 2 Flow chart.

107 duplicate papers were eliminated. After further screening, 407 studies were selected for reading titles and abstracts, of which 373 were excluded for various reasons.

Reasons for exclusion included studies not related to AI, systematic reviews about engagement but not containing AI, descriptive studies, studies that assessed engagement with traditional techniques and studies where the theme was not related to the aim of the systematic review.

Finally, in the eligibility phase, 34 papers were read in full, 19 of which were excluded for reasons detailed in Figure 2. A total of 15 papers were deemed eligible for inclusion in the present review.

3.4 | Data extraction

The first author performed two searches in each database corresponding to the search terms and applying the inclusion criteria. Once the results were obtained, they were downloaded and sent to the second author. Each author read the title and abstract of each of the articles separately and selected a total number for full-text reading.

3.5 | Coding agreement

To determine interrater reliability, Cohen's kappa (Cohen, 1960) was used to determine agreement between the two authors on two occasions. Each author made her selection, and subsequently, a meeting was held to discuss discrepancies and resolve difficulties. The agreement between the two authors was $\kappa = .89$. Once agreement was reached, 34 texts were selected, which were also read by both authors to determine which articles should be included in the review. Among all the articles, several disagreements were resolved after sharing the motivations of both authors. In this case, the agreement between the two authors was analysed and was $\kappa = .82$. Finally, the few disagreements between the authors were resolved by discussion in the meetings, and all the articles were included by consensus.

4 | RESULTS

4.1 | General question

The results related to the general research question about the objectives of research using AI for the study of engagement are reflected in Table 4. The table is based on the work of Heckler et al. (2022). This table lists the objectives of each study, as well as the types of analysis carried out in the articles. Each combination includes a group of studies represented according to the date and authorship of the publications. The objectives detail the purpose of the publication, while the type of analysis refers to which AI models were used to achieve these objectives.

AI has been used in the study of engagement for a variety of purposes. Five main objectives were identified in the review. The first and fourth objectives are better represented: to generate new items related to the assessment of engagement through self-report measures (13%) and to improve the prediction of levels of engagement experienced (13%). The second and third objectives accounted for 40% of the total sample, namely, to assess engagement levels through feedback from survey processes (20%) and to analyse the relationships between engagement and other variables (20%). The most frequently stated goal was to use AI to predict engagement levels (33%).

TABLE 4 Research objectives in the application of AI.

Objectives	Type of analysis	Author/date
Generate new items for improvement or create self-report engagement instruments through feedback in response to surveys	Linguistic analysis	Athukorala et al. (2020) and Ford et al. (2018)
Assessing the level of engagement through comments in response to surveys	Linguistic analysis	Garg et al. (2021), Liu et al. (2020) and Speer et al. (2022)
Knowing the relationship between engagement and other variables	Regression analysis	Al-Nammari et al. (2023), Chug, Vibhuti (2017) and Del Pozo-Antúnez et al. (2021)
Improved prediction of engagement levels	Visual analysis	Chang et al. (2018) and Zhu et al. (2020)
Predicting engagement levels	Linguistic analysis	Belhekar et al. (2020), Golestani et al. (2018), Shami et al. (2015), Tanaka et al. (2021) and van Roekel et al. (2023)

For studies that aim to detect and create new items to include in a self-report measure of engagement through written language in open-ended questions, Ford et al. (2018) administer a self-report instrument to a sample of more than 30,000 employees, where they also include an open-ended question to obtain information to include the key words of the answers as new items. To achieve their goal, they collect all the information obtained from the answers to the open-ended questions, and using ML software (WordStat), they group unique words and phrases and extract new items with the most frequently occurring words and phrases. They found that some items derived from the application of the technique worked as effectively as those developed using traditional methods. The technique identifies possible themes for new items in the engagement scale, thus generating some usable items covering engagement that had not been addressed in the existing scale. Athukorala et al. (2020) aim to automatically convert a comment given in an open-ended question included in a self-report measure into a numerical value based on the sentiment shown in the comment so that, in the future, engagement can be automatically scored through the employee's comment to the open-ended question. To do this, they administer a questionnaire to employees in an information technology company to determine what terms and types of comments are used in a self-reported measure of employee engagement. To run the model, they administer a self-report measure with open-ended questions on engagement and ask employees to rate each of the comments they write from 1 to 5, with 1 being 'little' engagement and 5 being 'a lot' of engagement. The results obtained from both the commentary and the scoring are used to construct a word dictionary in which each word has a corresponding value, depending on the previously given score. The comments from the initial questionnaire are subjected to a series of NLP techniques to increase the accuracy of the algorithm. The individual words are placed in the search dictionary with their corresponding values so that each time an open-ended question is asked, the answer comments are automatically scored according to the model. Using this technique, the *Employee Engagement Survey Generator* is created by converting the employee's comment to an open-ended question into a direct engagement score. This allows the administrator to know the level of employee engagement with high accuracy and directly, without having to read every single comment.

Regarding the assessment of engagement through comments in self-report instruments, Garg et al. (2021) aim to understand employee engagement by applying deep natural language learning concepts to comments collected in self-report measures called pulse surveys (short and precise surveys of one or two questions that are administered on a frequent basis). This type of survey is administered to employees on a biweekly or monthly basis. Employees are asked to write their comments, which are then evaluated using NLP by identifying the most relevant keywords and phrases. The model they create has the ability to evaluate comments quickly and accurately by summarizing the text, thus providing an overview of employee engagement through text analysis without the need for individual reviews of each comment. Liu et al. (2020), to achieve their goal, administered a self-report measure that, in addition to Likert-type response format items, contains open-ended questions. In this way, structured and unstructured data can be obtained. In the first case, multiple ML models are used to obtain the direct engagement score of the quantitative self-report measure. In the second case, to determine the level of engagement through unstructured data, they apply the sentiment analysis technique, specifically with the *Google Cloud NLP API* tool, to the comments that employees respond to the open-ended questions on engagement. This tool analyses the language of the comments using data that already exist in the API and adds an engagement score based on the comment. The authors find that both AI techniques provide insight into whether employees have a higher or lower level of engagement depending on both the score on the self-report instrument and the words used in the open-ended question. Speer et al. (2022) aimed to assess work attitudes and perceptions, including engagement, through comments generated by participants in response to surveys on work attitudes and perceptions. NLP algorithms were applied to analyse and score participants' comments related to engagement. The analysis of these open-ended comments allowed us to measure the presence and level of engagement expressed in participants' responses, which provided valuable information about employees' emotional, cognitive and behavioural connections to their work. Therefore, through the evaluation of the comments in response to the surveys, it was possible to analyse and measure the level of engagement of the participants, which contributed to a deeper understanding of their attitudes and perceptions of work in the study.

Among the studies that focus on studying the relationship between engagement and other variables, Al-Nammari et al. (2022) seek to identify and understand the organizational factors that significantly influence employee engagement. To answer these questions, researchers have used AI- techniques, specifically ML algorithms such as random forest (RF), gradient boosting (GB) and extra trees (ETs). These algorithms analyse data collected from hospital-level National Health Service staff survey data and assess the relative importance of different organizational factors on engagement. By applying these algorithms, they can identify complex patterns and nonlinear relationships between organizational factors and engagement. This AI-based methodology provides a quantitative way to identify the key drivers of staff engagement in healthcare settings. Del Pozo-Antúnez et al. (2021) presented a dual objective: to quantify to what extent the variables of the *Job Quality Index* (JQI) explain engagement scores and to determine which variables of the JQI most affect engagement scores. To do so, they assess the relationship between engagement and job quality using the self-report instrument JQI. By means of a nonlinear multidimensional index (based on ML), they relate engagement scores to the seven JQIs. Engagement is influenced mainly by the social environment index, and similarly, the skills and discretion index and perspectives are also crucial in promoting engagement. In the same vein, Chug and Vibhuti (2017) seek to understand the relationships between engagement and organizational culture and between engagement and individual communication by applying ML techniques. To do so, they administer a self-report instrument to identify factors that make up culture and communication. The direct scores on this self-reported measure were analysed using a regression model (GMDH), which assesses the relationships between these two concepts and engagement. The authors find that one of the factors most related to engagement is receiving positive personal feedback, especially from supervisors, so employees who receive more positive feedback experience higher levels of engagement.

For studies aimed at improving engagement prediction, Zhu et al. (2020) proposed a novel automatic prediction model based on hybrid deep models. For the model to predict engagement levels, they generated a dataset composed of fragments of videos in which each video was assigned a score according to the intensity of engagement considered by the subjects' nonverbal language. Once all the videos have been collected, a pre-established recurrent neural networks (RNN) model is trained and then tested on videos in which the model has never been shown to predict engagement well. The results suggest that the model can predict engagement based on nonverbal language, such as facial cues, and that the proposed method provides significant improvements in engagement prediction. A very similar study is that of Chang et al. (2018), who propose a model that aims to improve engagement prediction. To do so, they also use a dataset labelled according to the intensity of subjects' engagement in different videos. To predict this, they used an ensemble model composed of three conventional cluster-based models and an attention-based RNN model reinforced with heuristic rules. Finally, they found that with the RNN model, they can provide useful information about when a subject tends to have low levels of engagement. The results indicate that the proposed methods effectively improve the performance of engagement prediction using nonverbal language.

Finally, among the research that has focused on predicting the level of engagement, Belhekar et al. (2020) do so through other variables related to well-being. The authors assess employees who are exposed to constant physical risk (in this particular case, they work in the care of tigers) by administering several self-report measures on wellbeing-related concepts (satisfaction, perceived safety, job characteristics, resilience, etc.). The results of these self-report measures are analysed using CART (classification and regression trees). When they determine which variables best predict levels of well-being, they regress the well-being and satisfaction variables to predict levels of engagement. Their results show that based on these two variables, engagement can be predicted. Golestani et al. (2018) presented a model that takes advantage of ML techniques to analyse and predict employee engagement. Their aim was to test the effectiveness of the model in identifying important words and phrases for engagement prediction. They use data from an annual self-report measure of engagement and text written by employees on a public network within the company to create a dataset that is labelled according to its phrases and words in a binary way. Data where engagement is not perceived are scored 0 and 1 for those where it is. This dataset is used to create the first ML model (the naïve Bayes multinomial method and an optimization process). In the first step, the model is created with the given data and tested to predict engagement with data that have not yet been trained, such as self-reported measures from later years. They then compare the model's output with what is actually obtained in the self-report measures. Their model helps to identify specific words and phrases used by employees that play an important role in predicting engagement. Shami et al. (2015) set out to clarify whether engagement can be predicted more effectively through social networks than through demographic data from self-report measures, as has been done thus far. To test this, they use a stepwise regression algorithm that compares the messages written on social networks and the score of the self-report measure. They argue that social media can increase the ability to predict the level of engagement. On the other hand, they indicate the minimum number of social media posts needed per employee to make a reliable prediction and which dictionaries are predictive of employee engagement. Similar results were obtained by Tanaka et al. (2021), who aimed to determine whether engagement can be predicted by the frequency of conversation and/or content. To determine, they create an ML model, specifically BERT, which they combine with NLP, in which they include all the content that employees write in corporate tools and the frequency of these conversations. Their results revealed that engagement can be predicted not by the content of the messages but by the frequency with which they communicate, that is, the more frequent the messages they send and the more frequent the communication they maintain, the higher the level of employee engagement. With an objective similar to that of a previous study, Van Roekel et al. (2023) aimed to classify employees into categories of high or low engagement. To do so, they collected self-narratives through surveys, to which they applied text mining techniques to extract linguistic and psychological characteristics. They used different classification models, such as naïve Bayes and RF models, to classify employees into categories of high or low engagement by analysing the linguistic and psychological characteristics present in self-narratives. The most relevant textual characteristics for classifying engagement were identified, thus confirming the usefulness of text mining in organizational research.

A summary of the objectives of each study, their types of analysis and their results are detailed in Table 5.

4.2 | Specific questions

4.2.1 | What were the sources of the data used to feed the AI models?

The studies reviewed have not been homogeneous in terms of the data they have obtained and the sources they have used. The data used for the reviewed studies can be divided into structured data and/or unstructured data (Del Pozo-Antúnez et al., 2021; Ford et al., 2018; Golestani et al., 2018).

Structured data refer to standardized self-report questions that are administered to company employees, and they must answer them by choosing between different standardized options (usually in Likert-type response formats). This type of data was collected from a total of 12 publications. Unstructured data come from different types of sources: on the one hand, open-ended questions, self-narratives and comments (Speer

TABLE 5 Analysis of the characteristics of studies that use AI for the study of engagement.

Title	Author (year) localization	Data	Algorithm/ type of AI	Aims/research questions	Findings	Benefits
Real-time prediction of employee engagement using social media and text mining	Golestani et al. (2018) Orlando, USA	Social networks and self-report measurement	ML and NLP The Naïve Bayes Multinomial method and an optimization process	Determine the level of employee engagement by analysing all the information they post on a public network within the company. Compare the results of a self-reporting measure that they pass each year with what is described on social networks	The textual analysis model used predicts engagement by identifying specific words and phrases used by employees	Provide managers with data on employee engagement levels, which they can use to improve organizational health
Text mining narrative survey responses to develop engagement scale items	Ford et al. (2018) Washington, USA	Self-report measure and open-ended questions	ML– WordStat software	Writing new items that can be part of an already standardized scale through participants' responses to an open-ended question	Four new items derived from the open-ended questions are created which function in the same way as those elaborated with traditional methods and which had not been addressed in the existing scale	Assist other researchers to develop items to improve assessment scales
Business intelligence assistant for human resource management for IT companies	Athukorala et al. (2020) Colombo, Sri Lanka	Self-report measure and open-ended questions	DL-LSTM	Automatically convert a given comment in a self-report measure into a numerical value based on the sentiment shown in the comment, so that you can automatically score the engagement on given comments in future self-report measures	The Employee Engagement Survey Generator converts the employee's comment to an open-ended question into a direct engagement score	Know the level of employee engagement with high accuracy and directly, without having to read every single comment
Promoting work engagement in the accounting profession: a machine learning approach	Del Pozo-Antúnez et al. (2021) Córdoba, Spain	Self-report measure – *Job Quality Index*	ML– Regression models	To measure the relationship between work engagement and job quality and identify the components of job quality that most affect the engagement concept	The work engagement index is mainly influenced by the social environment index. The indexes of skills and discretion and outlook are also crucial in the level of engagement	Help HR staff to propose efficient strategies that improve both individual well-being and overall company performance
Multirate attention based GRU model for engagement prediction	Zhu et al. (2020) New York, USA	Dataset	DL–CNN	Improving engagement prediction using a novel automatic prediction model based on hybrid deep models	The model used predicts engagement based on nonverbal language, such as subjects' facial cues, suggesting that this method provides significant improvements in predicting engagement	Help HR staff to detect through this type of language what the level of employee engagement might be
i-Pulse: A NLP based novel approach for employee engagement in logistics organization	Garg et al. (2021) Lonere, India	Self-report measure	NLP	To determine the level of employee engagement through their responses to a self-report measure called a pulse survey	The model employed has the ability to provide deep insight into employee engagement through analysis of the text of survey comments	Helping managers understand their employees' concerns

TABLE 5 (Continued)

Title	Author (year) localization	Data	Algorithm/ type of AI	Aims/research questions	Findings	Benefits
Using HR analytics to support managerial decisions: A case study	Liu et al. (2020) Kennesaw, USA	Self-report measure and open-ended questions	NLP–Google Cloud Natural Language Processing API	Analysing engagement through responses to self-reporting questions and their comments	The scores given on the self-report instrument and the question answered can predict the level of engagement	Guide HR professionals in making decisions regarding employees
Enhancing employee engagement through a novel mathematical model in the hospitality sector of India	Chug and Vibhuti (2017) Chittorgarh, India	Self-report measure	GMDH model and AI-DL	Predict engagement through other variables such as organizational culture and individual communication	Employees who receive personal feedback, especially from their supervisors, have comparatively higher levels of engagement	To help managers better understand and address the psychological state and behaviours of their employees
Inferring employee engagement from social media	Shami et al. (2015) Nueva York, USA	Self-report measure and internal social networks	Text mining–stepwise regression algorithm	To determine whether the frequency with which employees write posts on the company's social networks and the content of these posts is related to the level of engagement	The number of posts and their content can predict the level of engagement	Provides more real-time information on engagement, enabling organizations to address engagement issues faster
Estimating work engagement from online chat logs	Tanaka et al. (2021) Tokyo, Japan	Corporative tool	ML–BERT	To determine whether the level of engagement can be predicted by the frequency with which employees speak and their relationships with colleagues rather than by the content of their messages	Engagement depends more on how often people talk than on the content of the conversation	Help managers with information to make decisions (internal rotation of employees based on engagement levels)
An ensemble model using face and body tracking for engagement detection	Chang et al. (2018) Shanghai, China	Dataset	ML–DL (CNN)	Improving the detection of engagement with an ensemble model composed of three conventional cluster-based models and an attention-based RNN model	The proposed methods effectively improve the performance of nonverbal language engagement prediction	Help HR staff to detect when an employee has low levels of engagement
Guarding the guardians: understanding the psychological well-being of forest guards in Indian tiger reserves	Belhekar et al. (2020) Mumbai, India	Self-report measure—*The Organizational Commitment Questionnaire*	CART models	To determine through the administration of self-report measures the perception of engagement, satisfaction, security and well-being	Engagement is predicted by wellbeing and job satisfaction	Helping HR to make decisions regarding employees
Turning words into numbers: Assessing work attitudes using natural language processing	Speer et al. (2022)	Open-ended comments	NLP and transformers	Develop, validate and deliver NLP algorithms capable of analysing employee engagement from open feedback	Analysing and measuring participants' level of engagement, which contributed to a deeper understanding of their attitudes and perceptions of work	Help researchers discover patterns, themes and sentiments in textual data that may not be evident with traditional manual methods

(Continues)

TABLE 5 (Continued)

Title	Author (year) localization	Data	Algorithm/ type of AI	Aims/research questions	Findings	Benefits
What is work engagement? A text mining approach using employyees' self narratives	Van Roekel et al. (2023)	Self-narratives	ML–Random Forest and Naïve Bayes	Classify employees into categories of high or low engagement. through self-narratives in response to surveys, using text mining techniques to extract linguistic and psychological characteristics	The most relevant textual characteristics for classifying engagement were identified, thus concluding the usefulness of text mining in organizational research	The data obtained provides valuable information for managers to better understand the needs and concerns of their teams
Exploring drivers of staff engagement in healthcare organizations using Tree-Based machine learning algorithms	Al-Nammari et al. (2022)	Self-report measure	ML–Random Fores, Gradient Boosting, Extra Trees	Identifying and understanding the organizational factors that significantly influence engagement through the application of AI techniques	Identify complex patterns and nonlinear relationships between organizational factors and engagement	Enhance decision-making in healthcare management

et al., 2022; van Roekel et al., 2023) that are included in addition to self-report measures, internal company social networks, and corporate tools such as Slack (Tanaka et al., 2021). In addition, some research has used both types of data (structured and unstructured) to obtain information. Specifically, three studies used self-report measures and open-ended questions (Athukorala et al., 2020; Ford et al., 2018; Liu et al., 2020), and two studies used self-report measures and internal company social networks (Golestani et al., 2018; Shami et al., 2015).

In addition to these types of data, two investigations conducted in a more controlled context use videos of other subjects to construct datasets with which to train the model (Chang et al., 2018; Zhu et al., 2020). Table 6 summarizes each study considering the type of data used.

4.2.2 | What AI techniques have been used to study engagement?

As shown in Table 7, the two main AI techniques that have been used are ML and NLP. However, some studies combine both for more complete results. This would be the case for Golestani et al. (2018), who, in addition to using a specific ML technique called naïve Bayes for the classification of self-report measure scores, also use NLP to analyse everything employees write on internal company social networks. Another study applying both techniques is that of Athukorala et al. (2020), who used NLP to analyse the answers to open-ended questions and added an LSTM (long-term memory algorithm, which is a type of convolutional neural network) to improve the recognition of the text provided in the open-ended questions. Using both techniques, Liu et al. (2020) used a multiple ML model to analyse the structured data and an NLP model to analyse the text of the open-ended question. Garg et al. (2021) used ML to preprocess the text of answers to open-ended questions and NLP to obtain the most relevant words and phrases about engagement. Tanaka et al. (2021) used ML-only models, specifically BERT, which is an attention mechanism that learns the contextual relationships between words in a text and is applied to NLP to determine how much employees talk and about what, using corporate tools to predict engagement. Speer et al. (2022) also used ML models such as transformers and NLP algorithms capable of scoring texts based on important employee attitudes and work perceptions, including engagement.

Table 7 shows that in the total number of studies reviewed, all of them used ML; however, NLP was used only together with ML on seven occasions, and none of them were used exclusively.

Regression models were used in six of the studies. Del Pozo-Antúnez et al. (2021) used a regression ML model to determine the relationship between engagement and job satisfaction based on the results of a self-report measure. Something very similar is done by Chug and Vibhuti (2017) using a regression model called GMDH that analyzes the relationships between organizational culture variables and individual communication to predict engagement. Shami et al. (2015) used an automatic stepwise regression procedure called stepwise regression. By scoring the results of a self-report measure, they seek to determine whether what employees write on internal company social networks predicts the levels of engagement experienced. Belhekar et al. (2020) used a different model. They use an ML model, specifically CART models, to regress two

TABLE 6 Types of sources and data used in the engagement study.

Study	Type	Structured data	Unstructured data
Golestani et al. (2018)	Social networks and self-report measurement	X	X
Ford et al. (2018)	Self-report measure and open-ended questions	X	X
Athukorala et al. (2020)	Self-report measure and open-ended questions	X	X
Del Pozo-Antúnez et al. (2021)	Self-report measure	X	
Zhu et al. (2020)	Datasets	X	
Garg et al. (2021)	Self-report measure	X	
Liu et al. (2020)	Self-report measure and open-ended questions	X	X
Chug and Vibhuti (2017)	Self-report measure	X	
Shami et al. (2015)	Self-report measure and internal social networks	X	X
Tanaka et al. (2021)	Corporative tool		X
Chang et al. (2018)	Datasets	X	
Belhekar et al. (2020)	Self-report measure	X	
Speer et al. (2022)	Open-ended comments		X
Van Roekel et al. (2023)	Self-narratives		X
Al-Nammari et al. (2022)	Self-report measure	X	

TABLE 7 AI techniques used to study engagement.

Study	NLP	ML	Type of ML
Golestani et al. (2018)	X	X	The Naïve Bayes
Ford et al. (2018)		X	Classification model
Athukorala et al. (2020)	X	X	DL – LSTM
Del Pozo-Antúnez et al. (2021)		X	Regression model
Zhu et al. (2020)		X	DL – CNN
Garg et al. (2021)	X	X	DL
Liu et al. (2020)	X	X	KNN, LG, RF, GRB, DT
Chug and Vibhuti (2017)		X	GMDH
Shami et al. (2015)		X	Stepwise regression
Tanaka et al. (2021)	X	X	BERT
Chang et al. (2018)		X	DL – CNN
Belhekar et al. (2020)		X	CART
Speer et al. (2022)	X	X	Transformers
Van Roekel et al. (2023)		X	RF and Naïve Bayes
Al-Nammari et al. (2022)		X	RF, GB, ET

Abbreviations: BERT, bidirectional encoder representations from transformers; CART, classification and regression tree; CNN, convolutional neuronal network; DL, deep learning; DT, decision tree; ET, extra trees; GB, gradient boosting; GRB, gradient boosting tree; KNN, K-nearest neighbours; LG, logistic regression; LSTM, long short-term memory; RF, random forest.

variables on the level of engagement. Al-Nammari et al. (2022) used RF, GB and ET regression models to identify the relative importance of each organizational factor in predicting staff engagement and to better understand how these factors influence engagement.

However, classification models were used in two studies. Ford et al. (2018) used an ML model called WordStat software, which classifies an employee's level of engagement based on the answer they have written in the open-ended question of a self-report measure. Van Roekel et al. (2023) used ML algorithms to classify employees' self-narratives into categories of high or low work engagement based on text characteristics.

Finally, the application of DL techniques has been employed in the work of Chang et al. (2018), who used a ML model (convolutional neural networks) for engagement detection, and Zhu et al. (2020), who used an already trained DL RNN model.

4.2.3 | How has the use of AI benefited the study of engagement?

The results obtained from this research have had positive consequences in at least three different areas. First, results have been proposed to help managers manage their employees. Second, they provide support to human resources staff in their decision making, and finally, they provide new research findings. The contributions of these studies are presented in Figure 3.

The use of AI for the study of engagement allows company managers to assess the level of engagement of their employees and to assess the events and reasons that form the basis of the engagement experienced in their company. The use of these techniques, in addition to predicting engagement levels, can provide managers with data on the engagement levels of their employees, which they can use to improve organizational health. The data obtained provide valuable information to better understand the needs and concerns of their teams (van Roekel et al., 2023), offering the opportunity to get to know their employees better and interact with them, initiate new programmes or stop those that are not beneficial in the employees' opinion (Golestani et al., 2018). The use of AI can enable managers to be aware of real-time data, which can provide them with an overall snapshot of their company's well-being and help them understand the concerns of their employees (Garg et al., 2021). It can help them identify challenges and directions for action, such as placing employees in internal rotation processes depending on the level of engagement (Tanaka et al., 2021). Ultimately, managers can better understand and address the psychological state, attitudes and behaviours of their employees in relation to work, and as a result, organizations can invest more in those factors that have the greatest weight in achieving a higher level of overall employee engagement (Chug & Vibhuti, 2017). In addition, healthcare helps managers and decision-makers make informed decisions on resource allocation and prioritization of efforts to improve staff engagement. By understanding the key drivers of staff engagement, organizations can focus on the areas that have the most significant impact on employee satisfaction and performance (Al-Nammari et al., 2022).

In addition to providing benefits to managers, AI could be used by HR professionals to propose efficient HR strategies that improve both individual well-being and overall company performance (Del Pozo-Antúnez et al., 2021). The use of AI not only allows us to understand or predict engagement but also provides relationships between variables. This is reflected in work such as that of Liu et al. (2020), who found negative relationships between engagement levels and turnover. HR professionals are interested in investigating why such data are available, which could help them make decisions regarding those employees (Belhekar et al., 2020). Additionally, knowledge of nonverbal language (movements such as head scratching, body turning, facial cues, gaze direction, etc.) can help HR staff detect engagement levels through nonverbal language (Chang et al., 2018; Zhu et al., 2020).

Ford et al. (2018) believe that this approach, with some improvements, can be useful for other authors using self-report measures. They can develop items to improve instruments, and customized measures can be created with high accuracy (Athukorala et al., 2020). This method can potentially complement self-report measures, thus providing more real-time information on engagement and allowing organizations to address engagement issues more effectively (Shami et al., 2015). In addition, researchers can gain a deeper understanding of engagement by uncovering patterns, themes, and sentiments within textual data that may not be readily apparent through traditional manual methods (Speer et al., 2022).

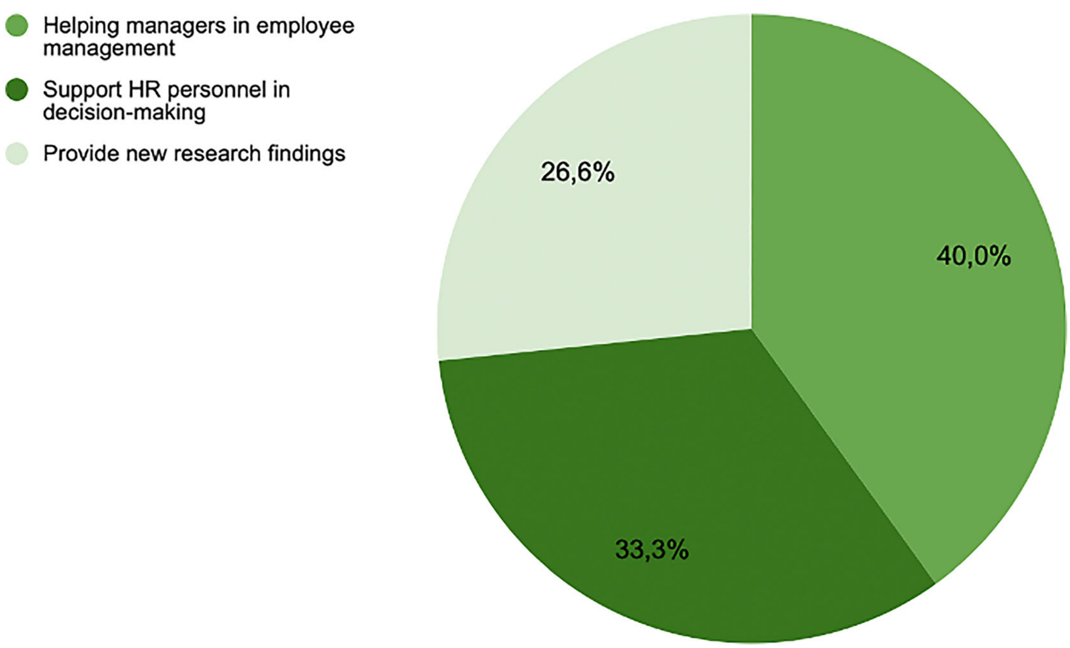

FIGURE 3 Percentage of positive consequences pertaining to each of the three spheres.

4.2.4 | What model accuracy has been achieved in the different studies?

Of all the research reviewed above, only six of the studies have provided the level of accuracy of the models used, so we cannot compare all the models reviewed thus far. As shown in Table 8, the accuracy values provided in some of the studies range from very high levels, such as Athukorala et al. (2020), to very low levels, such as the classification model of Ford et al. (2018). The study by Ford et al. (2018) used a classification model with only 22.4% accuracy. However, classification models such as the naïve Bayes method have shown better results, with accuracies of 74% (Golestani et al., 2018) or 61% (Liu et al., 2020).

The prediction models, on the other hand, obtained high levels of accuracy (73%, 77% and 83%; Liu et al., 2020), while the logistic regression model obtained somewhat lower accuracy (62%; Liu et al., 2020). Undoubtedly, the models with the best accuracy percentages were the DL models with accuracies of 71% (Chang et al., 2018; Zhu et al., 2020) and 87.48% (Athukorala et al., 2020). Van Roekel et al. (2023) used RF and naïve Bayes classifiers. The RF models had varying accuracy scores: unigrams (52%), bigrams (53%), psychological features (60%), and linguistic features (54%) 19. When using the naïve Bayes classifier, the accuracy scores improved for unigrams (64%), with slight improvements for bigrams (56%), psychological features (61%), and linguistic features (55%) compared to the RF results. Overall, the model accuracies achieved ranged from 52% to 64% for classifying employees into high or low work engagement.

4.3 | Statistical questions

4.3.1 | Which countries have the studies been carried out in?

Although all the papers were published in English, the geographical area in which the research was carried out varied. Of the 15 papers included in the review, eight were carried out in the United States and India. In the first case, the cities where the research was carried out were Orlando (Golestani et al., 2018), Maryland (Ford et al., 2018), Newark (Zhu et al., 2020), New York (Shami et al., 2015), Kennesaw (Liu et al., 2020) and Detroit (Speer et al., 2022). In India, studies have been conducted in Mumbai (Belhekar et al., 2020), Lorena (Garg et al., 2021) and Chittorgarh (Chug & Vibhuti, 2017).

The remaining four papers were published across other regions of the world, including the cities of Colombo (Sri Lanka; Athukorala et al., 2020), Cordoba (Spain; Del Pozo-Antúnez et al., 2021), Tokyo (Japan; Tanaka et al., 2021), Shanghai (China; Chang et al., 2018), Utrecht (The Netherlands; van Roekel et al., 2023) and Abudabi (EAU; Al-Nammari et al., 2022). Figure 4 shows the geographical influence on the origins of the studies.

4.3.2 | What has been the temporal evolution of the number of studies?

As shown in Figure 5, although there was an increase in the number of studies published between 2020 and 2021, the distribution was not linear. It is likely that the editorial policy followed when publishing studies does not correspond to a real reflection of the studies carried out. In other words, the year of publication does not always coincide with the year in which the study was conducted or the year in which the publication was submitted.

TABLE 8 Accuracy of each model.

Study	Algorithm	Accuracy
Golestani et al. (2018)	The Naïve Bayes (classification model)	74%
Ford et al. (2018)	Classification model	22.4%
Athukorala et al. (2020)	DL – LSTM	87.48%
Zhu et al. (2020)	DL – CNN	71%
Liu et al. (2020)	KNN, LG, RF, GRB and DT	61%, 62%, 83%, 73%, 77%
Chang et al. (2018)	DL – CNN	71%
Van Roekel et al. (2023)	RF and Naïve Bayes	52%–64%

Abbreviations: BERT, bidirectional encoder representations from transformers; CART, classification and regression trees; CNN, convolutional neuronal network; DL, deep learning; DT, decision tree; GRB, gradient boosting tree; KNN, K-nearest neighbours; LG, logistic regression; LSTM, long short-term memory; RF, random forest.

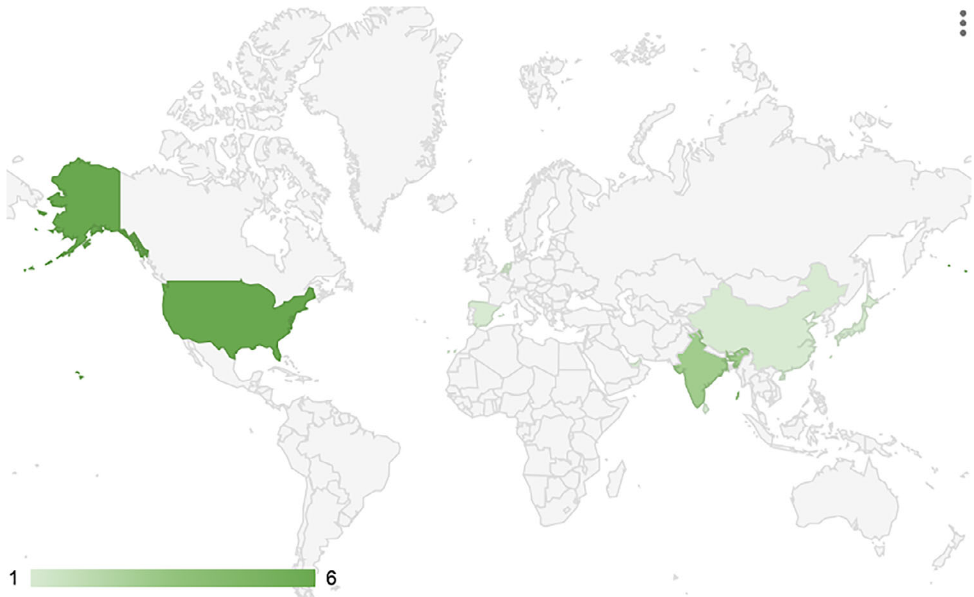

FIGURE 4 Geographical areas where the studies were carried out.

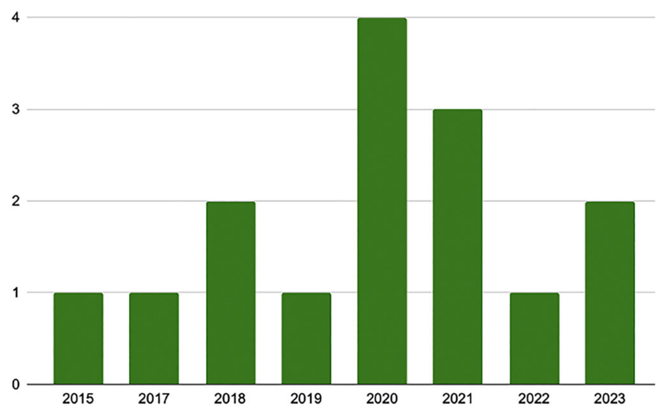

FIGURE 5 Number of articles published per year.

5 | DISCUSSION

The aim of this review is to determine what studies have been published thus far on the use of AI to study engagement to understand the state of the art. To date, engagement and AI have been studied separately according to their main areas of expertise: psychology and engineering. However, although in recent years there has been a growing interest in studying how AI can be used to benefit the field of psychology, there are few studies that apply it to engagement.

The objectives proposed by the different studies reviewed point to a clear trend toward the assessment of engagement levels through AI techniques (ML and NLP), ranging from the generation of items through comments on open-ended questions included in self-reports to the creation of new instruments to assess engagement. In other words, all the research contributes directly or indirectly with new findings to determine the level of employee engagement in an innovative way. The findings relate to the adoption of measures to address some of the many limitations not only of measuring engagement in particular but also of assessing engagement through self-report measures in organizational contexts (Golestani et al., 2018). According to Garg et al. (2021), these methods also help to eliminate the possibility that those correcting and interpreting self-report instruments incorporate biases in the way comments are classified and interpreted. Therefore, this may be consistent with most of the literature reviewed having employed linguistic analysis to achieve their goals, as language can reflect how the senders wish to be perceived and does not bias the information obtained when responding in a directed manner to item questions (Loveys et al., 2017).

This review indicates that through AI, comments that employees make in different formats about their work can be transformed into structured information through ML and NLP and become new engagement items to be included in existing self-report measures. In addition, NLP can be used to evaluate the language of comments, and ML classification models can be used to classify comments into engagement scores. Through ML regression models, it is possible to determine the relationship between engagement and other variables, and with the use of DL, it is possible to improve this prediction.

With these AI techniques, it is possible to predict engagement through other variables related to well-being, self-reported measures, self-narratives, and the content of corporate tools.

The results of our review indicate that most of the data used to study engagement have been extracted, as has been done thus far in other studies addressing other concepts or variables, from sources such as social networks and response text to open-ended questions included in self-report measures (Hall, 2020; Tsugawa et al., 2015). The text extracted from these sources allowed for linguistic analysis due to the heterogeneity of the data sources used in the different studies. In addition, the study by Tanaka et al. (2021), in which data are extracted from texts written by employees in corporate work tools, a finding that has never been reflected in other studies thus far, stands out for its novelty.

Regarding the most commonly used models for the study of engagement, the data confirm what is known thus far: ML and DL are the two main AI techniques used to study psychological concepts; however, in the case of engagement, another technique, NLP, has also been used. This is because the algorithms of both techniques can quickly transform large volumes of structured and unstructured text data into actionable information. Thus, through NLP, the analysis used by ML algorithms is strengthened (Kumar et al., 2021). This could explain why of all the studies analysed, the model with the lowest accuracy used an ML classification model but did not include NLP.

Moreover, this integration of NLP with other datasets or even other algorithms has enormous potential for organizations (Verma et al., 2021). Companies can incorporate structured and unstructured data from various sources (both quantitative and qualitative) to understand variables related to organizational health or even create customized action plans to provide concise information to managers (Tran, 2018).

The results of the research analysed are similar, as they have provided positive consequences in at least three different organizational domains, including providing managers with guidelines for managing their employees and decision support for HR personnel. This finding is in line with Teniwut and Hasyim (2020), who indicate that decision support for HR personnel improves business processes and outcomes, in addition to increasing the efficiency and profitability of the firm as a whole. The results of this review reveal clear and concise information on the benefits of using AI in the study of engagement, as these results indicate that AI can benefit both companies and employees, as well as research.

These findings support the first objective, which was to compile the relevant studies prevailing in the field of AI in relation to the use of ML and NLP models for the prediction of engagement levels, as well as the methods applied and the results obtained.

This accuracy has not been equally important in all research, since not all studies have shown its level of accuracy. However, of all the articles analysed, although the levels of accuracy are uneven among them (very high or very low), we can see that the DL models are the ones that obtain the highest accuracy. However, although the model that shows a lower accuracy is classification (Ford et al., 2018), when a classification model is used with NLP, a higher accuracy is obtained (Golestani et al., 2018). These results suggest that when both techniques are used together, higher accuracy is obtained.

In relation to the statistical questions, it is important to note that the literature review shows limited geographic diversity in the publication of the articles examined, with studies conducted in the United States and India being predominant, which together make up more than half of the sample. The remaining studies were distributed proportionally among five other countries. This phenomenon could indicate a relatively low level of interest from the research community in the study between engagement and AI. Therefore, we could consider that the lack of attention to this topic can be attributed, in part, to the great complexity of approaching engagement through the analysis of language. This is supported by the fact that the number of studies has not grown over time either. This may be because, in the early years, when this type of issue began to be studied, AI models for studying psychological constructs in general were not well developed; however, at present, more complete studies could be counted on those that have been carried out in the field of organizational psychology, especially on engagement (Speer et al., 2022; van Roekel et al., 2023).

These questions allow us to answer the second objective of the research: to determine the state of the art of ML and NLP models in relation to the study of engagement.

In summary, the study of engagement through AI techniques is beginning to develop, and the techniques that seem to be most effective are ML and NLP through both structured and unstructured data, the former obtained through self-report measures and the latter through social networks, open-ended questions and corporate tools. These results, in relation to engagement, are in line with previous research that has studied other psychological concepts, such as depression or personality factors (Alexander et al., 2020; Stachl et al., 2020; Tay et al., 2020). Specifically, in terms of engagement, this study has shown that the main techniques used for ML studies and NLP when used to study engagement have benefited both HR managers and managers in the management of employee organizations, as well as researchers, by providing novel ways to create new items for existing or direct measures. It has also provided insight into the evolution of publications over time and the geographic areas of influence in conducting related studies.

However, while it is true that, as a result of this research, many of the questions posed at the beginning can be answered, it is also possible to draw from these results future lines of research toward different approaches to engagement prediction, thus solving the third objective of this research.

In most of the studies analysed, specifically in 5 out of 15, AI has been used to predict engagement levels, so future research could be oriented to the prediction of engagement levels or scores. The use of AI began with studies that applied text mining (Shami et al., 2015) for prediction and then evolved toward more developed techniques, such as the naïve Bayes multinomial (Golestani et al., 2018) and CART (Belhekar et al., 2020) methods. Two of the most recent studies, in addition to ML techniques, also apply NLP (Speer et al., 2022; Tanaka et al., 2021) to study engagement; therefore, these studies could reveal a clear trend in combining the use of both ML and NLP techniques to predict engagement. However, the study by Tanaka et al. (2021), although earlier in time, is more novel than the study by Speer et al. (2022) because of the way in which the data were extracted. Although at a technical level both studies use very similar techniques (transformers and NLP), Tanaka's data extraction is more novel, as it is based on text from corporate tools, something never seen before.

The fact that both studies present interesting results with the combination of both techniques could suggest a new line of research with two new approaches, on the one hand, the application of a BERT language model and, on the other hand, the collection of text from corporate tools. In addition to studies focusing on language, there is research that predicts engagement based on nonverbal language. This finding could lead to a future line of research, leaving language aside and focusing on nonverbal analysis with AI techniques and using previously labelled datasets.

5.1 | Limitations and future lines of research

We must take into account the small number of studies that have been included in the review in relation to studies related to other areas of psychology. Although there were studies in different countries around the world included in this systematic review, the inclusion criteria indicated that they had to be published in English or Spanish, so there could be other interesting studies in other languages that were not included. For the level of accuracy, it has been difficult to find information on this, as many of the studies did not show it, so conclusions on this aspect should be made with some reservation.

Regarding the level of accuracy, it has been difficult to find information on this subject since many of the studies did not show it, so conclusions on this aspect should be made with some reservation. However, those studies that have indicated their accuracy have very different results. The accuracy of the models was not consistent, since some of them presented less than 25% accuracy, while other models obtained more than 70% accuracy. Therefore, future studies could consider the use of several classification models for subsequent comparisons in terms of accuracy. It would be useful to use other classification models and check whether the problem of low accuracy lies in the type of model itself or in other factors. Therefore, it would be a challenge for a future study to develop an AI model that uses ML and NLP techniques and achieves a higher accuracy than those shown thus far.

The studies reviewed have not been homogeneous in terms of the data they have obtained and the sources they have used. The data used for the reviewed studies can be divided into structured data and/or unstructured data. However, although there are studies that have used both types of data, none of them have proven which of the two is more effective in extracting information about engagement; therefore, for future studies, it would be interesting to compare with which of the two types of data the most fruitful results are obtained with AI. It would also be interesting to conduct further studies using unstructured data (e.g., text collected from blogs, corporate tools, social networks, etc.) to analyse language with other AI techniques that have not been analysed in this study, for example, large language models such as the large language model (LLM).

In terms of benefits, at the research level, Ford et al. (2018) believe that this approach, with some refinements, may be useful for other self-report measure researchers developing items to improve measurement scales, as well as allowing for the creation of customizable self-report measures with high accuracy (Athukorala et al., 2020). For future studies, the question can be raised as to whether this method would be useful for potentially complementing self-report measures, thus providing more real-time information on engagement and allowing organizations to address engagement issues faster.

The results on the location where the articles were published and the years of publication suggest that the articles reviewed are recent and published in very specific parts of the world, which makes us think that the lines of research mentioned to develop in the future may uncover a new field of study between the two disciplines.

5.2 | Conclusion

This systematic review covers studies in terms of the use and application of various AI techniques, such as machine learning algorithms and NLP, to study engagement.

This approach provides a sequential way to understand the various trends of these algorithms being used in the study of engagement along with their advantages and disadvantages.

The results of different studies are extracted to identify the research trends in ML and NLP for the study of engagement, and new lines of research are proposed that can cover the limitations found.

In this systematic review, 407 studies were collected from different psychology and engineering databases, and 15 studies were selected (those that met the inclusion criteria) for consideration.

The study showed that 15 of the 15 selected studies used AI ML techniques for the study of engagement, and 7 of them also used NLP. These studies are the last to be carried out chronologically, which indicates that the future trend will be the union of both techniques. The results indicate that the best studies in terms of level of accuracy are those that use only ML (although those that use both techniques also obtain good engagement scores). This suggests a number of questions that have not yet been addressed and may provide new lines of research to help future researchers work on these challenges.

As part of future work, the authors expect to increase the number of studies that generally use AI for the study of engagement. However, it is particularly expected that they will use the ML technique, as it appears to have the highest accuracy, although NLP is also expected to be included in these studies. This is because recent studies suggest that the vast amount of language data available from social networks, blogs, corporate tools, and so on, can be utilized for exhaustive analysis. This analysis allows for the determination of employee engagement levels through language use, eliminating the need for self-reporting instruments. Consequently, this addresses the main challenge posed by the limitations of these instruments.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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How to cite this article: García-Navarro, C., Pulido-Martos, M., & Pérez-Lozano, C. (2024). The study of engagement at work from the artificial intelligence perspective: A systematic review. *Expert Systems*, *41*(11), e13673. https://doi.org/10.1111/exsy.13673