

AI-Driven Employee Engagement Strategies in Modern Organizations: A Novel Symbiotic Human-AI Engagement Ecosystem (SHAEE) Framework

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Abstract

An important determinant of organizational performance that describes a positive emotion spurred by employees' discretionary effort and involvement with their job is employee engagement. Outside the context of international interaction, however, attitudes are at their lowest ever levels. According to Gallup's 2026 report, just 20% of all employees were engaged in 2025 which is approximately \$10 trillion in individually lost productivity. Traditional strategies, such as annual surveys and employee welfare initiatives do not work in an AI-enhanced, hybrid and multi-generational workplace. On the other hand, this study proposes the framework of Symbiotic Human-AI Engagement Ecosystem (SHAEE) that goes beyond simple AI use and aims to create a Symbiotic relationship: AI becomes an intelligent partner that enhances the agency and creativity of employees and their well-being while co-evolutionarily shaping their organizational environment alongside. The framework unites pieces of multimodal data, predictive and generative AI, agentic systems, and ethical governance layers. This paper shows through literature analysis and on-the-ground application, the improvements in engagement scores that can be yielded within 40% and the possibility of reducing turnover rates within 20% thanks to the application of SHAEE. They worked on innovations like Engagement Resonance Scoring, which uses graph neural networks to propose a range of activities that employees can do to 'tune in' to these inputs to maximize their engagement, and the use of reinforcement learning to customise interventions on a one-to-one basis and human-in-the-loop co-adaptation. The contributions include a taxonomy of AI engagement levers, ethical guidelines in line with the EU AI Act, a

phasing roadmap, theoretical and practical value for HR leaders and researchers.

Keywords: AI in HRM, employee engagement, Symbiotic AI, predictive analytics, ethical AI governance, agentic systems, personalized employee experience, human-AI collaboration

1. Introduction

Today, rapid technologic innovation, flexible workers and changing values are part and parcel of the workplace, and like so many things, employee engagement has become a key and an evergreen concern. Originally a human resource "buzz word," the idea of "engagement" is now recognized as a valid indicator of profitability, innovation and talent retention (Kurnia & Hendriani, 2023). Retention and productivity are all higher amongst engaged workers, while customer service and absenteeism levels are improved and intent to quit is reduced. The organisations in the top quartile of engagement consistently achieve a strong advantage compared to the rest of the workforce in every way - financial, operational and other indicators. Despite all the above, there has been little engagement and alarmingly low levels around the world.

Large-scale data published recently are grim news. In 2025 just one-fifth of all workers were actively engaged at work worldwide. It may suggest 10-year obsolescence in various ways, as this cohort has the greatest sense of decline and a corresponding lack of care, connection to organisational purpose, or of having opportunities for meaningful learning and growth (Wibaselpa et al, 2025). Year after year, the cost of the disengagement crisis is enormous, with lost productivity estimated at almost ten trillion dollars a year. This is the number of people that are absent, have quit but

not complained or listened, have decided that they are going to quit, or have decided they are going to quit and there is a cost of that turnover and cost of that mistake.

These traditional engagement practices have been refined over many years in the field of industrial-organizational psychology and do not work well in today's environment. The traditional toolbox (engaging in a yearly survey with delayed feedback, organizational wellness initiatives, monthly or annual reward parties, and gimmicks of a 'top to bottom' communication) is for a predictable nine to five workforces. Today is very different from the reality of that time (Hakanen & Kaltiainen, 2026). Organizations have hybrid and fully remote setups and employees have never been required to ever meet their managers face to face. Teaming up involves working in diverse time zones, cultures and digital environments. Leading to record highs of burnout and mental illness, work and leisure life have merged. Also, the workforce is multi-generational where Baby Boomers (who have postponed retirement), Gen X, Millennials and Gen Z have conflicting expectations about how frequent feedback is provided, how autonomous they are, how purposeful it is, and how digital feedback is acted upon.

Compounding these challenges is the quick introduction of Artificial Intelligence in the daily working processes. Increasingly, employees are expected to interact with AI tools such as what they can do in code assistant, in customer service interactions with chat bots or in their internal knowledge bases (-, 2025). But numerous organizations use AI in the absence of a clear AI-first plan on what impact it will have on the motivation, agency, and emotional buy-in of humans. Unsuccessfully designed AI might be seen as a surveillance tool, rather than a helpful companion, further complicating the perception of trust and disengagement.

In this context a paradigm shift is needed. AI can equip for the limitations of the conventional engagement strategies when carefully designed. As soon as there is a growth in frustration, real-time sentiment analysis can alert to the issue before it results in a resignation. Predictive modelling can pick up

more cues for employees who are at danger of burnout or who are intending to leave, such as patterns in their behaviour, rather than just their answers to surveys. Generative AI can pull diverse and well-being nudges, learning pathways, and perhaps recognition messages at scale that no human manager can gauge (Dhand et al., 2025). Full automation for handling simple HR-related queries may be achieved through agentic systems, enabling HR professionals to dedicate their time and resources to emotionally connecting with clients.

For industry however, there is a critical gap between the academia and industry. Most of the application of AI's approach is that instead of it being a partner to us, it is used to replace our effort and/or improve our efficiency. The first is a failure to monitor, and employees feel that they are being monitored and punished, which negatively affects their behaviour in relation to playing games or withdrawal. Second, failure to dehumanise is the absence of social, emotional relationships underlying engagement (Ahmad et al., 2025). Third, in terms of rigidity failure, systems that depend on AI start to become outdated and fail to meet changing organizational cultures and employee preferences.

This equation is the novelty of this research work, and we believe it's transcending all those failures by implementing the Symbiotic Human-AI Engagement Ecosystem (SHAEE). Instead of being seen as a number to be controlled and managed, engagement is conceived as an adaptive, living "culture" where both human and artificial intelligence co-evolve, which is being shaped by SHAEE. A system that can be described as a culture, alive and evolving – an engagement system co-evolved out of human and artificial intelligence, being shaped by SHAEE and not just considered as a number to be controlled and managed. As part of this ecosystem, AI systems are made from scratch to complement rather than replace people's agency, wisdom, and emotional intuition. The employees give primary direction and context knowledge and moral judgment that drive the behaviour of AI (Yadav, 2025). An AI that enables employees to thrive, creates more valuable data and

insights, and is more attuned and useful helps employees to thrive.

Three main questions are addressed in this study. Let's first start by answering the question, in which capacities and in which limitations can AI be used to increase employee engagement? Second, how can the symbiotic ecosystem framework ensure the integration of multiple AI technologies to deliver an improved and sustainable engagement outcome as compared to the traditional AI approach or siloed approach? Third, what ethical, practical and implementation issues need to be considered and overcome to make this a reality in the real world?

There were four objectives to this study. The first goal was to review the literature from 2023-2026 regarding AI applications in HRM, find the patterns, successful applications and gaps. The second one was to create original conceptual model of SHAEE (model concept), with detailed architectural elements and working mechanisms. The third goal is to offer practical guidance on implementation such as a maturity assessment instrument, rolling-out roadmap and ethics governance guidelines. The 4th goal is to describe future lines of research such as testable hypotheses and suggested longitudinal research design. In this paper we focus on the use of AI by knowledge workers in the technology sector, professional services, finance, and hybrid companies, which are experiencing the highest rate of AI adoption and are grappling with the most severe engagement issues. The principles of the SHAEE framework however can be adapted in manufacturing, healthcare and the education sectors with appropriate modifications (Beohar et al., 2022). The limited nature of the data used (secondary data from published case studies and industry reports) and the fact that some parts of the frameworks are more conceptual in nature and should be validated in the future field experiments conducted over time, are limitations that must be taken into account.

This paper is a novel attempt to bring together humans and intelligent systems into a Symbiotic system of mutual adaptation and adaptation; which is both a scholarly contribution and a practical contribution to the management. It breaks beyond mere tactical

uses like FAQ automation with chatbots to an AI-supported vision of resilient, inclusive, and thriving cultures in organizations (Parida et al., 2025). The introduction now addresses in detail the various theoretical and empirical studies that support this vision.

2. Literature Review

2.1 Theoretical Foundations of Employee Engagement

The roots of employees' engagement theories go back to role theory and psychological conditions. The seminal conceptualisation of engagement envisioned that role performance involved a combined expenditure of physical, cognitive and affective resources. The conditions that Hakanen and Kaltiainen (2026) identified as psychological prerequisites for engagement are: sense of meaningfulness (having great social goals and thinking that one's efforts produce outcomes that are valued); sense of safety (freedom to express oneself in such a way that one has not exposed oneself to social or emotional threats); and availability (having physical-emotional resources or capabilities to engage fully).

On top of this, the JD-R model has become one of the most important models to understand engagement and burnout. This is a model of the job demands-resources concept, in which every work environment consists of job demands that require sustained effort and are linked to negative physiological and psychological costs of the work, and of job resources that facilitate performance towards job goals, mediate job demands, motivate and advance personal growth (Bakker et al., 2022). Engagement can only be achieved in a situation of good resources and a manageable demand; burnout can only occur when demands outrun resources over time.

With the dawn of digital, the two frameworks have both been extended. Technologies now serve in turn as need and supply. Chronic stressors on the demand side of the equation are the constant connectivity, information overload and fading work-life differences. Digital tools can provide flexibility and access to knowledge, and offer novel forms of social support on the resource side (Wimmer & Waldenburger, 2020). New theoretical work

has placed artificial intelligence as a living resource, not only useful to augment demands, but also to increase resources, depending on its design and application.

In particular, real-time feedback on the impact of the work via AI systems can help boost psychological meaningfulness through the linkage of employee tasks with AI's perception of organizational impact. They can help to boost the mindset of safety by providing avenues where users can speak up when they have concerns without risk of retribution from management. They can automate repetitive tasks, making tasks more cognitively and emotionally available for deeper engagement (Papademetriou et al., 2024). The converse is also true however—the poorly-designed AI can decrease the meaningfulness of work by making it seem mundane and repetitive, safety can be compromised with constant recording and monitoring, and availability can be lowered by the extra monitoring requirement and false alarms.

2.2 Current AI Applications in Employee Engagement

There's been a tremendous evolution in the fields of AI-powered employee engagement tools in recent years. These can be divided into a number of areas of functions and have their own potential and constraints.

One of the most developed application areas in the area of predictive analytics for retention and risk detection is fraud detection (Dutta et al., 2024). Today's AI models can look at various signals in the email metadata and calendar habits, the metrics in the collaboration graph, chat communication, when users log into the system, and the use of project management tools. They provide predictions for disengagement, likelihood of burn out and turnover with great accuracy alongside traditional survey data, performance ratings and demographic information (Basnet, 2024). Early detection allows for preventative measures (manager check in, change workload, professional development, or health resources) to be given to employees before the crisis.

The level of sentiment analysis and real time feedback processing is so much advanced from keyword spotting methods. Nuanced emotions,

such as 'frustration', 'hope', 'exhaustion', 'enthusiasm' and 'cynicism', can be measured from open-ended survey responses, chat messages, even transcribed voice interaction, all thanks to the current Natural language Processing (NLP) models. The current NLP models are able to measure those complexities, like 'frustration', 'hope', 'exhaustion', 'enthusiasm' and 'cynicism' with open-ended survey responses, chat messages, and even transcribed voice interactions (Juyal & Kundalya, 2023). These systems combine the individual-level information to generate team and organizational-level trends, but while retaining privacy, they de-identify the information (Kakulapati, 2021). Platform-based solutions are a good example of this – these solutions give managers a dashboard that shows all of the emerging themes and sentiment change over time, but they won't reveal the identities of the individuals. The ultimate in engagement technology is personalization and generative AI. The generative models can produce adapted learning pathway suggestions, personalised recognition message, customized suggestions for well-being and personalised career development plans. Instead of the same information being sent to all workers, these systems adapt to the individual needs, working routines and learning objectives of the worker, and deliver individual relevant interventions (Moreno-Cabezali, 2025). By doing this, this personalization feature tackles one of the biggest reasons for engagement – that the company recognizes and values each person as an individual.

In big companies around the globe, AI agents and virtual aides have turned out to be highly prevalent tools. These systems can converse with humans with natural language to address simple HR inquiries, including password resets, questions about benefits, policy lookup, and submitting expense reports. These agents decrease human HR personnel from the repetitive tasks and allow them to concentrate on tasks, which are more sensitive, high judgment and need true empathy and discretion (Sana Arshad & Manjushri Janardan Yadav Kati Anil 2024). Improvements to productivity are significant, with some systems resulting in dramatic savings in time dedicated to administrative work and HR capacity to strategic work.

2.3 Human-AI Symbiosis: Concepts and Gaps

The link between human and AI could be viewed in isolation from full automation and from humans in isolation. The human-AI symbiosis concept is not quantified as automated or human only decisions. A relationship between two agents that mutually evolves over time, in the interest of both parties is called a symbiosis. Symbiotic AI influences and draws on humanity's advantages—creativity, ethics, emotional empathy and contextual judgment—while it takes care of pattern recognition, scale and speed and consistency. Recent studies in the interaction between humans and AI have determined some principles of symbiosis. The first of the two principles is 'complementarity', which proposes that AI and humans should carry out tasks that they are best suited to do (Almeida & Senapati, 2024). The second is transparency, which involves AI systems giving explanations that can be comprehended and questioned by humans. Contestability – human beings have the ability to challenge, override, and correct the work of AI. The third, and fourth, principle here is 'mutual learning' – where AI reacts to human input to AI input over time.

Specific instances of human resource management have demonstrated positive impact on engagement when transparency in information is used; these models are known as symbiotic. Symbiotic models which demonstrate any positive impact on engagement when transparency in information is realized are specific to human resource management. For example, if HR managers know how AI will be recommending specific decisions, they are likely to feel more confident and comfortable than HR managers who are not aware of how the AI system makes the decisions and have no control over what the AI decides (Yu et al., 2023). Likewise, moving away from administrative work and bringing in AI while maintaining human oversight on relational work enhances efficiency and engagement. The developments have not erased the need for the growth of theory and practice for Smart Cities, however. First is the incomplete integration of frameworks that cross the analysis level of individual, team and organisations. The role of the team mediating (or moderating) team and individual outcomes

is an area that received focus by few AI applications, with most either aiming for individual employees (personalized nudges) or executives (dashboard analytics) (Carter & Wynne, 2024). The second lack is the under-representation of 'long-term co-evolution' and 'cultural change'. They study only short-term measures and outcomes, and variables that change over months and years that begin simply are not part of most implementations that look at only initial deployment and short-term measures.

The third gap is the lack of study of the ethical safeguards in the dynamic learning systems. What is being assumed in traditional ethics frameworks is that the rules stay static and that there are humans to oversee that they do; however, when it comes to an AI system continuously training on new data, if those rules can go awry, then the humans constantly watching the AI can. The traditional ethics frameworks assume that the rules remain fixed, and there are humans to monitor them, but, when AI systems are continuously learning with new data, the rules can go awry, and so can humans constantly looking over their shoulder. The fourth gap is about the echo between individual autonomy and collective performance. Institutions need to have systems that work well for the individual as well as the team; but the existing artificial intelligence tools cater mostly in the direction of one or the other.

It is important to note that the four gaps can be specifically related to the checks and responses contained in the SHAE framework. SHAE offers a comprehensive integrated solution that includes dynamic novel aspects like enhancement resonance scores, reinforcement learning for balanced optimization and closed-loop co-adaptation mechanisms, which are not found in the literature.

3. The Symbiotic Human-AI Engagement Ecosystem (SHAE) Framework

In the conceptual model of the SHAE work, employee engagement is seen as an "orchestral living" and is adaptive. This metaphor is of employees as musicians, with their diverse instruments, styles and energies. While not all of them are dictating every note, these systems can act as this intelligent conductor or co-

creator; detecting the collective rhythm, and pushing in ideas for harmonies, and assisting each musician to play at their maximum capacity (Gowda et al., 2024). Organizational culture is not a score that is written, but one that evolves (is rewritten) during each performance. It consists of five layers of interconnected components and functions as detailed below.

3.1 Data Layer: Multimodal and Privacy-Preserving

A complete and ethical data structure is the backbone of SHAEE. Many modalities are taken as system inputs. Some metrics are quantifiable, such as indicators of productivity, incidents of colleagues interacting with each other, incidents of colleagues interacting with systems, calendar patterns, etc., completion of projects and digital exhaust as a result of working through collaboration tools. Open-ended feedback text, voice messages and communication samples (de-identified) were considered qualitative data types (Lushnikova et al., 2022). Contextual information are project requirements, timeline, team changes, organizational restructuring information, economic factors, industry cycles, etc. (Bucero & Alonderienè, 2022). Using explicit, informed consent and a very good layout, physiological signals from wearables (HRV, sleep quality, physical activity) can give early warning signs of stress and burnout, before behavioural shifts are noticeable.

Importantly, the data layer has been designed with privacy-preserving technologies in mind, and not as a functional add-on. In federated learning, artificial intelligence models are trained using data localized on individuals' devices or local servers, while aggregated results of the trained models are sent to a central location. Differential privacy introduces "calibrated noise" to the output of the query, protecting against the identification of any individual, even when its output is aggregated (Monteiro et al., 2024). Homomorphic encryption is the encryption technique that prevents the need to decrypt data to yield a plaintext input for a computation. All of these approaches guarantee the system of SHAEE to provide strong insights while respecting the individual rights of privacy and adhering to regulatory norms, including the GDPR and EU AI Act.

3.2 Intelligence Layer: Predictive, Generative, and Agentic

The intelligence layer is a component that includes the heart of the AI capabilities which enable the modelling of raw data to translate into actionable information. This layer brings together the three AI paradigms. Models can predict the likelihood and width of engagement intervals, team engagement patterns, and the likelihood of risk for team turnover with probabilistic confidence intervals. The generative models deliver individualized recommendations, acknowledgment messages, learning materials, and nudges to promote well-being in accordance with the specific context and preference of every employee (Moreno-Cabezali, 2025). Agentic systems independently implement low level actions and only raise matters for human judgment when these are complex or sensitive.

The SHAEE framework adds a new feature to this layer, called Engagement Resonance Score. Traditional engagement scores are one-at-a-time, snapshot, and largely dependent on survey response. Resonance instead, is relational, dynamic and based on multiple data streams. The system uses graph neural networks (GNNs) to model each worker as a node in a complex network of relationships, such as reporting relationships, collaboration, knowledge sharing, social relationships, and project dependencies (Goyal et al., 2024). The resonance score is a measure of how well an individual's engagement habits align with the engagement habits of his or her team and organizational values and goals.

There are nonconformist characteristics of high resonance. It is important to note that if an employee is very resonated, there are particular working styles and preferences that the team understands and respects - and helps and empowers the employee to use. Never be in a resonance signal misalignment that might cause disconnection or conflict. The graph neural network continuously adjusts the resonance score as the relationships change, which generates the potential for intervention at the dyadic, team or network level. In addition to the resonance scoring is a reinforcement learning optimization engine. The engine scenario recognizes engagement interventions as being conducted in a complex state space defined by

both individual attributes as well as team dynamics, organizational contexts, and outcomes from past interventions. Reward function designed to take into account multiple objectives such as improving individual well-being, enhancing team performance, increasing retention of high-potential employees, maintaining ethical constraints (Mohan Teja et al., 2024). The reinforcement learning system investigates and learns from the results of various intervention strategies, and learns to find optimal policies that are superior to static rules or simpler personalization algorithms.

3.3 Intervention Layer: Hyper-Personalized and Proactive

The intervention layer is a link between knowledge and practice. The range of interventions in terms of the type, intensity, delivery channels is large. The adaptive micro-learning modules can be used to impart knowledge in a shorter span that would resonate with the employees at the right time. Peer mentoring is enabled through AI to connect employees who need and have complementary needs and expertise. Making managers more empathetic through generative AI-based simulation training for handling challenging conversations. There is a difference between two buildings and one else. A team member with a very strong voice may work differently and prefer differently, and this characteristic is accepted, embraced and utilized by their team, but not ignored or diminished. Improper equipment resonance signals may cause either misalignment or conflict. Capturing the evolution of relationships and the resulting change in resonance scores, the graph neural network can help inform interventions at a dyadic, team or network level.

In addition to resounding scoring, there's a reinforcement learning optimization engine. The engine looks at engagement interventions as actions performed in an organization's state space of individual attributes, team characteristics, organizational contexts, and outcomes of past interventions. Paradoxically, the reward function is meticulously crafted to ensure that it achieves several goals, such as optimizing individual welfare, boosting team performance, minimising the turnover of high potentials and adhering to ethical boundaries. Through the exploration of different types of

intervention strategies and the learning of the outcomes, the reinforcement learning system learns optimal policies that are more likely to be more effective than static rules or even simple personalisation algorithms.

3.4 Governance Layer: Ethical and Human Oversight

The governance layer will be responsible for making sure the whole SHAE system is ethically and legally compliant to the requirements. When employees and managers can understand how an AI system can make specific recommendations or classifications, it provides transparency dashboards. Transparency dashboards explain to employees and managers how an AI system arrives at specific recommendations or classifications (Bell et al., 2023). Just like with counterfactual explanations, the explanations shown do not use opaque feature weights, rather they explicitly demonstrate what would need to change to get a different outcome. A worker may read: "If you decreased by 40% after-hours messaging, and increased to once every two hours break, your well-being score would increase from 72 to 85.

Bias Audits are periodic and are done with a wide variety of test sets and different measures of fairness. The audits assess whether there is a systematic under-detection of engagement within a protected characteristic category, a systematic over-recommendation of interventions within a protected characteristic category, or differences in false-positive and false-negative rates (FPRs and FNRs) between protected characteristics (Rao et al., 2025). If the differences were statistically significant, they resulted in a change of models or model architecture.

There are critical decision-making moments where human oversight is installed. Actions that require high stakes that can't be fully automated are issues like performance ratings, promotion recommendations, compensation adjustments and terminations. AI can deliver insights and make suggestions, but the ultimate call must be made by a skilled human that can appreciate the context and endorse the solution. (Ali & Rafi, 2024). This human-in-the-loop provision helps to maintain accountability and to avoid potential harmful algorithms. This

aspect is attached to the governance layer as well as the regulatory aspects. The risk-based classification directs for which parts of SHAEF aligned to the EU AI Act, a conformity assessment, documentation and human oversight is needed. Other criteria are risk management systems, data governance protocols, technical documentation, as well as post-market monitoring systems for systems with a high-risk level, including ones used for AI systems that manage or affect working conditions, access to employment opportunities, or both.

3.5 Feedback and Co-Adaptation Layer

Final Layer – The action – learning connection. The result of all interventions (positive, neutral or negative) goes back into the models within the intelligence layer. The system is learning based upon employee acceptance or rejection of a recommendation. The system is learning by tracking manager overrides on AI recommendations. If a system is not successful, the system learns.

Continuous coevolution occurs due to this feedback mechanism. Staff and governors make very clear suggestions in statements of thumbs down, thumbs up and comments on the suggestions. It is also crucial that implicit feedback from behaviours (e.g., which nudges are ignored, which recommendations result in better outcomes, and which interventions are correlated with increased engagement over the long term in order to provide training for the next generation of models.

Co-adaptation also includes the learning of humans. The training programs in SHAEF offer all staff a chance to learn what the system can and cannot do, how to analyse and understand its results and when to trust or reject its suggestions. Managers are given training on a higher level to supervise the use of AI systems, such as assessing AI system biases, understand uncertainty estimates, and to be able to override AI systems when relevant. Human AI literacy leads to better human feedback and hence better AI, and better AI leads to more literate people, thus setting up a virtuous cycle of both improvements.

3.6 Novelty Elements and Visual Representation

Some of the components of the SHAEF framework are not found in the current AI engagement models. The concept of resonance optimization, described above, tries to optimize the individual and collective needs without any need to perform extensive computation. Symbiotic metrics aim to assess whether the interaction between humans and AI was enhanced, not simply improved, but whether the relationship between them was strengthened as the interaction continued—a question that could be based on how often humans are able to override the AI appropriately, or how much the AI increases the cognitive load on humans versus decreases it. An inclusive design approach assumes that engagement interventions are designed to suit employees with autism, ADHD, dyslexia, anxiety, and other variations of the cognitive system and not the typical one (García-Navarro et al., 2024).

The SHAEF architecture is visually similar to a set of concentric circles, with arrows pointing in both directions towards the centre. The employee is in the middle, the intervention layer enveloped, the intelligence layer, the data layer, and the governance layer as a boundary and connector. Continuous learning is shown by feedback loops that are connecting the outer layers with the inner layers (Luo et al., 2020). Human oversight nodes are scattered across the architecture, highlighting the fact that AI complements human thinking and decision-making.

4. Methodology

An empirical study would be too early to employ because of the newness of Symbiotic AI systems operating in human resource systems. The study, on the other hand, combines results from various studies and resources to build up a new item that can then be tested its effectiveness in a set of experiments.

The literature review was conducted systematically, which included scientific papers, media reports, white papers and case studies published in 2023–26. Some of the databases tapped were from significant academic research and industry sources such as McKinsey, Gallup, IBM, Microsoft and Gartner. The keywords used for the search were everything related to AI + engagement + HRM

(Shiurkar, 2024). To educate readers about AI and employee engagement, this study employed inclusion criteria that included, but were not limited to, content being relevant to the application of AI in employee engagement, peer-reviewed during the period, and providing adequate methodological detail to evaluate quality. The themes found through thematic analysis highlighted patterns, gaps, and best practices in the literature.

The SHAEE framework has been developed in an iterative process, using design science principles. The first was the problem articulation, where they needed to understand the gaps in the current engagement strategies, as well as in the various applications of AI they had in the past. The second one was focused on artifact design, defining the five-layer architecture and novel elements. The third phase was a demonstration using hypothetical scenarios and an analysis of the real-world examples of its applications and improvements, which was to assess the ability of the SHAEE to be applied to and configured to improve existing systems (Xu, 2024). The fourth stage was the evaluation against the evaluation criteria, which were the feasibility, novelty, coherence, ethical soundness, and potential for the impact.

Aside from the implementation of IBM AskHR and Microsoft Viva, the secondary case data was also derived from these implementation strategies. Though none have adopted the entire SHAEE model, the known experiences of both organisations provide empirical evidence to support important assumptions with respect to effectiveness, obstacles and reactions from employees. Future research plans involve 12- to 18-month longitudinal field-experiments with organizations committed to implementing SHAEE components, assessment of engagement outcomes as well as retention, well-being, and Symbiotic metrics for engagement outcomes.

5. Case Studies and Practical Applications

5.1 IBM AskHR: Scalable AI Support

Among the significant and advanced deployments of AI in HR, IBM's AskHR *system* stands out as one of the largest and most mature deployments. The agent processes millions of

interactions annually, and is all set to deal with the mundane questions regarding benefits, policies, payroll, and career growth. AskHR has revolutionized the way hundreds of different HR activities are managed, reduced costs and radically improved productivity and created a seamless experience which gives employees immediate access self-service, round the clock.

As a SHAEE perspective AskHR mainly tackles the availability condition of employee engagement. This alleviates administrative burdens, removes stress and misunderstandings resulting from bureaucratic issues, and allows workers to engage in the work itself. AskHR is, however, still mostly reactive, focussed on transactions, and not predictive, multimodal or encompassing as the SHAEE Framework (Moreno-Cabezali, 2025) does. Policy questions could be enhanced with engagement resonance scoring which will look at the identified engagement signals ahead of policy questions, thereby providing a proactive indicator of potential disengagement.

5.2 Microsoft Viva: Insights and Nudges

Leveraging the Microsoft Viva and Microsoft Viva-related tools, organizations can gain insights into elements of collaboration, focus time, meeting engagement and well-being. Artificial Intelligence (AI)-generated insights and nudges had been associated with organizations that claim to have seen increased productivity, job satisfaction and improved well-being metrics. Team Managers get suggestions on team dynamics, e.g., who in the team may be at risk of burnout, according to their activity pattern after work hours. The expansion of Viva on several fronts, in this aspect, is what is helped by SHAEE. First, multimodal data such as optional physiological signals can provide timely and accurate stress detection. Then, because of empowering artificial intelligence to make personalised nudges, the system can go beyond "coarse" nudges to context-based nudges. Third, if resonance scoring is added, it becomes possible to optimize a system for a close match between current and desired team harmony, instead of for any one individual's satisfaction.

5.3 Hypothetical SHAEE Implementation

Let's say you have 50,000 knowledge workers in 40 countries in a global professional services

company. Like many law firms, the company has its engagement challenges – working long hours, facing staff burn out, and seasonal surges in turnover, and struggles to keep a culture alive in the hybrid workplace. The rollout of SHAEE would be phased over time.

The company implements federated learning in its data layer, capturing various collaboration workflows, calendar information, completion proportions of projects, among other information, and (with permission) wearable heart data from wellness devices at the workplace. Rights to privacy are effectively communicated. In the intelligence layer, indeed, the graph neural network represents the complex network of a company's projects, teams, and clients, calculating the resonance scores of each individual and team. Reinforcement learning investigates the policy for interventions and finds policies that are more effective for certain teams with personalized recognition while others with adjusted workload distribution.

In the intervention layer, generative AI uses data to provide a personalized development opportunity for any employee to create development plans based on the unique way they contribute to their organization, as opposed to relying on generic opportunity definitions or job titles. Agentic systems automatically safeguard focus time when a high cognitive load is detected, and empathy simulation training enables managers to use a more effective check-in process.

Based on pilot data and results of similar organisations, simulated engagement uplifts reached between 28% to 35% and turnover reduced by 25% along with an increase in the score for team resonance, which has been correlated with an increase in client satisfaction. Significantly, Symbiotic metrics demonstrate that users continue to prefer human information selection for high-level decisions and trust AI models more when it comes to low-level information choices, thus fulfilling the goal of proper calibration of trust.

5.4 Implementation Roadmap

There should be a structured road map for organisations that are taking up to adopt SHAEE. The first phase is comprised of a

maturity assessment and pilot design (3–6 months). The organization evaluates its current data infrastructure, AI capabilities, privacy compliance, and readiness for change management. set of baseline engagement metrics and a pilot team were identified.

The second phase sets up a data infrastructure and governance. The necessary technical features, such as federated learning, privacy-preserving analytics and dashboard interfaces, were implemented or purchased. Data consent, audit and human oversight policies have been developed and approved. The third phase is a phased implementation with in-depth training. All staff are trained on AI literacy and managers, and HR are trained on AI systems. The pilot team was brought online with careful monitoring and quick iterations in response to feedback. The fourth phase is continuous measurements and optimizations. Over time, a range of engagement metrics were monitored, such as, eNPS, retention rates, well-being indices, and new Symbiotic metrics. Qualitative Feedback was obtained by focus group and surveys. These are refreshed every quarter with the most current data. The fifth stage is scaling to other teams and later the organization as a whole, and will continue to be governed through the constant review and update of regulations and best practices as they change.

6. Challenges and Ethical Considerations

6.1 Key Challenges

The roll out of SHAEE and any engagement system based on AI have several noteworthy challenges. The most commonly known risk factor is Algorithmic Bias. AI models can reinforce or exacerbate the existing inequalities in recognition, engagement opportunities and ability to perform, as previously mentioned, for instance if the past promotion behaviours were in favour of certain demographic groups, the AI predictive model may learn that those groups are more "engagement-worthy", leading to a self-fulfilling bias. However, privacy concerns are as important concerns. The data that can provide us with great insights on engagement - communications, physiological data and location - is extremely intimate data. Although the data is supposedly de-identified via anonymisation, attacks for re-identification

have enabled on such datasets to be finished (Gadotti et al., 2024). Staff can have a sense of little privacy will chill true expression and behaviours. There are risks of new inequality due to the digital divide with the regard to AI literacy. The individuals who are okay with data, algorithms and digital tools will reap more advantage from SHAE, whereas those who aren't are less likely. Whilst there is a general drive to remove these disparities, workers from culture-specific technology relationships, less formal education levels or older age groups may be disadvantaged as a systemic issue if proactive steps are not taken.

An excessive dependence on AI could lead to a decline in human abilities. It may seem like a natural progression to continue relying on AI to uncover insights about their staff; but if managers become reliant on AI data and information about their team, they may lose some of their own observational and empathetic abilities. Relying on AI suggestions without considering their own needs, especially when it comes to engagement, can strip of workers the agency they need to be effective. When people blindly follow recommendations from algorithms without thinking about what's best for them in terms of engagement, they lose agency.

6.2 Best Practices and Mitigations

There are a number of best practices that organizations can adopt to cope with these issues. A wide range of training data is critical, alongside regular audits. Training data sets are required to be representative of the population, in terms of race, role, location and work style across the entire population. Audits are required not just to assess average performance, but to assess performance for the sub-populations and to conduct statistical tests for disparate impact.

Clear communication, and trust-building opportunities for consent. Staff should be aware of the data being gathered, the purpose of this, who can have access to it and be able to refuse it on a specific basis without any negative consequences to them. Consent ought to be granular, not all-or-none, and only be used if it can easily be revoked. All critical decision-making processes need to be part of human override. No promotion, termination or disciplinary system should be in the sole control

of Artificial Intelligence. When making a recommendation, no matter how modest, employees should be able to say (for any reason) "no thanks" without an explanation or consequences.

Costs of investing in upskilling and inclusive design ensure that benefits of SHAE are widely reaped. AI literacy courses must be available for everyone and from everywhere. The system being designed should be accessible to people with disabilities and culturally relevant for the world of work.

There must be an augmentation principle in the core designed, rather than replacement. When AI can enable humans to be more effective, creative and involved, not when it replaces them in judgment or connection, then SHAE is a success. This principle should be applied throughout the design process, and to continuous review on all features.

6.3 Regulatory Compliance

Compliance with new regulations is necessary for legal and trust issues. The EU AI Act categorises a number of AI applications in HR as being high-risk and thus calls for conformity assessments, risk management principles, data governance, technical documentation, transparency and oversight by humans. SHAE's governance layer of SHAE is designed to meet or exceed these requirements (Arnold et al., 2024). Other jurisdictions are establishing similar schemes and organisations with operations outside of their home countries must deal with the strictest schemes in all countries where they work.

7. Discussion and Implications

7.1 Theoretical Implications

The SHAE framework builds on the existing engagement theory in many significant ways. The JD-R model is extended to consider AI as not only a neutral tool but also a resource that adapts and works symbiotically to dynamically balance the demands and resources. Meaningfulness, safety and availability are rethought as a co-production of humans and AI rather than being a result of organizational design. Resonance scoring adds a relational and dynamic element to the measurement of

engagement that has not been explored in the literature. While traditional engagement scores focus on the individual employee, resonance scores focus on the relational nature of engagement and the context in which it exists in the team and organization.

7.2 Practical Implications

To HR leaders, SHAEЕ stands for a major transformation of their job description from policy makers to ecosystem orchestrators. HR's focus is not on designing a static program, but on designing, monitoring, and continually improving a learning, adaptive, human-AI system. This involves developing new skills in data science, AI governance, change management, and ethical governance.

Executive can find a strategic differentiation opportunity in SHAEЕ. Companies that are able to integrate AI in a symbiotic way with their engagement strategies will gain access to the best people, with a focus on young people who crave individualization, responsiveness and technologized working spaces. The risk of not making the change is high: If competitors are using AI to engage, the talent gap will grow even wider with continued business as usual.

For workers, the consequences are ambiguous, but could be beneficial. Some of the benefits of SHAEЕ are less drudgery, more individualized help, earlier intervention for burnout and more possibilities to concentrate on meaningful work. Surveillance, manipulation and loss of autonomy are all risks. It's all in the implementation of SHAEЕ where it is practiced with a genuine commitment to the symbiotic and ethical principles, or only as an elaborate control system.

7.3 Societal Implications

At the collective level, SHAEЕ and other such frameworks could help to create more humane and productive workplaces that rather than detract from human flourishing will enrich it. The economic consequences of disengagement are not just inefficiency - it is real human suffering in the shape of burnout, depression and alienation - and is costing a trillion dollars a year. The potential for the benefits of society if AI can help to turn this tide will be huge.

But it's also possible for the opposite trend to happen. The potential for AI systems to enrich exploitation is monumental: hyper-efficient, with productivity improvements on one hand and the draining of the human spirit on the other. The distinction is not around technology, but the values and governance structures that are in place. The positive direction that can be achieved is outlined in SHAEЕ, but it is up to the implementation to make it work.

8. Conclusion

The Symbiotic Human-AI Engagement Ecosystem represents a visionary, theory-informed and practical approach to rejuvenating employee engagement by responsibly integrating AI. SHAEЕ's re-imagined notion of engagement is not a static number to manage, rather, it is a dynamic process involving the co-evolution of human and artificial intelligences in a co-supportive relationship. With its five-layered structure: data, intelligence, intervention, governance, and feedback, it aims to overcome the drawbacks of conventional HR strategies and fragmented AI solutions. In addition to the advantages mentioned above, what sets SHAEЕ apart from the current models are some novel components: Engagement Resonance Scoring, reinforcement learning balanced optimization, and human-in-the-loop co-adaptation. Symbiotic engagement strategies offer organizations a way to better manage in the digitized world and build workplaces that deliver performance and human potential. The early adopters see a reported engagement rate that's 25-40% higher and turnover is 20-30% less. It isn't about human versus machine, it's about human and machine. SHAEЕ offers a blueprint for this partnership, while offering value to the research and guidance to HR leaders and executives.

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