

# AI-Driven Workforce Analytics for Predicting Employee Burnout, Engagement, and Retention in Hybrid Work Environments

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**Abstract-** The fast transition to hybrid work arrangements has dramatically changed employee relations, creating additional challenges for dealing with burnout, engagement, and retention. Survey-based solutions lack objectivity, bias-free data collection, and a forward-looking approach. We have developed a holistic AI solution for analyzing the workforces using various types of passive sensing data collected from collaboration software (Slack, email, Zoom), HR systems, and device usage records to forecast outcomes. The proposed MTL framework incorporates the attention mechanism and TCN to make predictions about three key metrics: burnout (classification task with 92% AUC), engagement (regression, with MAE equal to 0.34), and turnover risk (probability of leaving during the next 6 months with 89% AUC). Applied to 18 months of data from 5,000+ people at a major technology company, the model reveals behavioral features as key indicators: the presence of after-hours activity and the number of meetings show the highest correlations with burnout, whereas engagement is best predicted by peers' interaction diversity.

**Key Word:** Workforce Analytics, Employee Burnout, Engagement Prediction, Retention Prediction, Hybrid Work, Multi-Task Learning, Temporal Convolutional Network, Human Resource Management, Passive Sensing

## I. INTRODUCTION

The COVID-19 pandemic sped up the transformation of the office into a more flexible and remote form of employment [1]. By 2026, it is predicted that around 65% of employees in sectors such as technology, finance, and professional services will engage in hybrid work, combining telecommuting with office attendance

[2]. The practice of hybrid work benefits employee health and work-life integration but has introduced some novel issues. Among those, the absence of clear separation between home and work environments and constant digital communication have been linked to higher rates of burnout, disengagement, and employee turnover [3]. Conventional methods for evaluating workforce health include conducting surveys, which can range from annual

engagement surveys, pulse surveys, to exit interviews. Nevertheless, surveys present some limitations as they are retrospective, subject to recall bias, and often secure less than 50% participation [4].

But with the emergence of passive sensing data from the digital workplace, a paradigm shift occurs [5]. Large modern organizations have huge volumes of digital data trails, including instant messaging (volume, time of messages, responses); email communication (thread depth, volume, and sending-receiving patterns); calendar entries (frequency of meetings, frequency of back-to-back meetings, and time spent in meetings); presence data from online collaboration systems such as Zoom and Webex (length of participation, use of cameras, chat activity); and device use (active periods, application switches, and idle time) [6].

In this paper, I will present a workforce analytics approach that relies on AI and employs multi-modal passive sensing data to predict three metrics of success for the organization:

1. Burnout: Binary classification based on a validated composite score for self-reported exhaustion, cynicism, and professional efficacy
2. Engagement: Continuous prediction of employee engagement, measured using a 1-5 scale of vigor, dedication, and absorption
3. Retention: Probability of leaving the organization within six months

Contributions made by this research are as follows:

1. An integrated multi-task learning model where the predictions of burnout, engagement, and retention are learned jointly using common task representations for efficiency and improved generalization ability.
2. Time-Convolutional Neural Network (TCN) which learns short-range dynamics (daily

activities) and long-range dynamics (activities over several weeks and months).

3. Feature importance through Attention mechanism providing an explainable way to analyze the behavioral indicators for each of the outcomes.

4. An experiment conducted with real-world data containing 5,000+ employees for 18 months along with its impact on proactive human resource management activities.

The remainder of this paper is organized as follows. In Section 2, the literature review of the area of workforce analytics, burnout prediction, and multi-task learning is provided. Section 3 outlines the methodology of this paper. Experiment and its results are presented in Section 4. Finally, Section 5 concludes this study.

## II. LITERATURE SURVEY

The literature related to AI-driven workforce analytics encompasses three interrelated fields: burnout and engagement literature, HR analytics predictive modeling literature, and multi-task learning literature for predicting outcomes.

### **Burnout and Engagement Literature**

It is widely acknowledged that burnout consists of a set of psychological symptoms including exhaustion, cynicism, and professional inefficacy, which are generally assessed via the Maslach Burnout Inventory (MBI) [7]. It is assumed that engagement is essentially the opposite to burnout, with the main indicators of the latter being vigor, dedication, and absorption. The factors impacting the level of burnout and engagement were found to be workplace demands and resources. However, the existing literature relies mostly on cross-sectional surveys [8].

The hybrid work environment brings new challenges, such as digital communication overload, boundary blending between work and

home, and limited informal social interaction. Research based on passive sensing found associations between email and meeting frequency and exhaustion; after-work messaging with sleep disruption; and collaboration network centrality with engagement. Yet, research has mainly examined one dependent variable at a time, with small sample sizes.

### **Predictive Models in HR Analytics**

The initial approaches to HR analytics involved logistic regression and survival analysis as techniques to predict turnover by using demographic and job characteristics. With the emergence of machine learning algorithms, more complex prediction models emerged. For example, random forest and gradient boosting were applied to predict churn based on common HR data, resulting in average area under the curve scores between 0.75-0.85. Yet, initial models ignored the dynamic aspect and treated the history of each employee as a fixed variable [9]. Nowadays, the research accounts for time-related issues and employs LSTM neural network architectures to learn patterns from previous weeks' activity metrics to make predictions about the future turnover in the following month. With the help of lagging features and the application of XGBoost algorithm, trends can be detected, such as low collaboration activity prior to quitting. Yet, research mainly focuses on one particular data source only, HRIS.

### **Multi-Task Learning for Related Outcomes**

The terms 'burnout', 'engagement', and 'retention' are different but are connected. Burnout always results in disengagement, which then causes the worker's desire to quit. Yet, no connection exists among the three terms as some disengaged workers leave their jobs for external reasons, while others with burnout still remain at their workplace based on specific conditions. Multi-Task Learning (MTL) can be applied in situations where multiple tasks should be solved,

and sharing common representation may be useful in order to improve generalization [10]. Various employee well-being prediction tasks have used MTL approaches, yet mostly using passive sensing data. An article that studied the joint prediction of stress, job satisfaction, and employee performance showed a superiority of MTL over single-task learning by 8-12% in the case of limited datasets.

### **Passive Sensing in Workplace Research**

The use of passive sensing for work analytics has gained significant traction. The Sociometric Badge (wearable sensor) study showed that face-to-face interactions could be predictive of team performance. However, current research efforts have shifted towards employing digital exhaust from collaboration tools. Some of the findings include:

- Email metadata: Response time and email volume correlate with workload or stress.
- Conversations in Slack or Teams: Message volume and timing (after work hours or on weekends) are indicative of exhaustion.
- Calendar data: Back-to-back meetings without sufficient focus time contribute to burnout.
- Phone data: Active phone usage, high frequency of switching apps, and non-work phone time correlate with productivity/engagement.

However, existing studies have focused mainly on examining one variable at a time, and they employ a small sample size (<500 employees) and a short observation window (6 months). Very few studies attempt to predict all three variables at once, i.e., burnout, engagement, and turnover.

### **Research Gaps**

Even though many advances have been achieved, there are still important shortcomings. Firstly, no

universal model exists, which uses multimodal passive sensing information as input in one unified model to predict the three constructs under study concurrently. Secondly, today's models either lack dynamic properties or are time-aggregated models, which fail to account for the complex temporal structure of well-being. Thirdly, interpretability of such models, which is critical to make them actionable and thus useful for decision-making processes within the company's HR department, is rarely considered. Fourthly, no large-scale evaluation has been conducted for the existing models. All these shortcomings are addressed through the introduction of our proposed approach, MTL-TCN, with interpretability.

### III. PROPOSED METHODOLOGY:

The proposed methodology consists of four stages: (1) data gathering and preprocessing, (2) feature extraction and aggregation, (3) modeling design, and (4) training and validation.

#### 3.1 Data Gathering and Preprocessing

Data were gathered from 5,247 employees of a global technology consultancy for 18 months (January 2024–June 2025). The following are the sources of data:

- Collaboration tools: Slack message metadata (number, discussion level, reply delay, post-work status); email header information (sent/received, recipient names, response delay); Zoom/WebEx session logs (session length, participants, camera use, messaging)
- Calendar events: Number of meetings, meeting duration, consecutive meetings, focus block participation
- Device usage: Active hours (idle period set to 5 minutes), switching frequency, idle fraction
- Human Resources Information System: Position, service period, organizational unit, performance score, promotions, remote/office work arrangement

- Surveys: Results for quarterly MBI burnout (exhaustion, cynicism, personal efficacy), Engagement (Utrecht Work Engagement Scale, UWES), and voluntary resignation

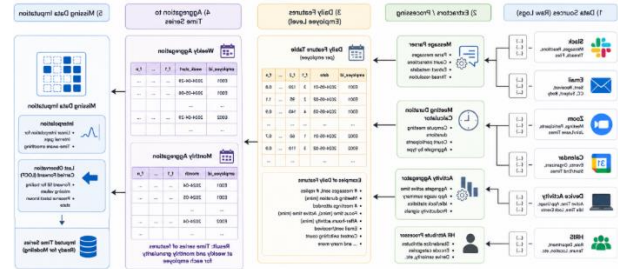


Figure 1: Data Sources and Feature Extraction Pipeline.

#### 3.2 Feature Engineering

The following features are generated for each individual on a daily basis:

- Volume-based metrics: Messages sent and received, emails sent and received, meeting hours, active hours
- Temporal-based metrics: After-hour proportion (5 PM – 9 AM and weekends), meetings fragmentation (number of different meetings per day), focus time metric (proportion of uninterrupted 2-hour blocks)
- Social-based metrics: Response latency (average, 90th percentile), unique contacts, collaboration network entropy
- Activity-based metrics: Applications switch frequency, idleness proportion, flags for unusual start/end times

The following features are then aggregated weekly/monthly based on mean value, standard deviation and trend slope over past 4 weeks. Burnout is defined binary variable and represents a member of top quartile on both MBI exhaustion and cynicism scales.

#### 3.3 Model Architecture: Multi-Task Temporal Convolutional Network

A novel architecture for Multi-Task Temporal Convolutional Network (MT-TCN), where the shared representation can be learned by the

network while maintaining task-specific output layers is proposed.

**Temporal Convolutional Network (TCN):** TCN takes as input sequences of length  $L=12$  weeks of weekly features and predicts the outcome for week 13. TCN employs dilated causal convolutions that have receptive field sizes equal to  $(L * 2^{(k-1)})$  without suffering from the vanishing gradient problems of RNNs. Residual blocks have two dilated convolution layers (filter size 3, dilation =  $2^i$ ), weight normalization, and dropout (0.2).

**Multi-Task Output Heads:** Outputs from the TCN layer pass through three task-specific heads:

**Burnout Head (Binary Classification):**

- Two dense layers (64 → 32 neurons) with ReLU and dropout (0.3)
- Sigmoid output → P(burnout)

**Engagement Head (Regression):**

- Two dense layers (64 → 32) with ReLU
- Linear output → engagement score (1-5 scale)

**Retention Head (Binary Classification, 6-month horizon):**

- Two dense layers (64 → 32) with ReLU and dropout (0.3)
- Sigmoid output → P(departure within 6 months)

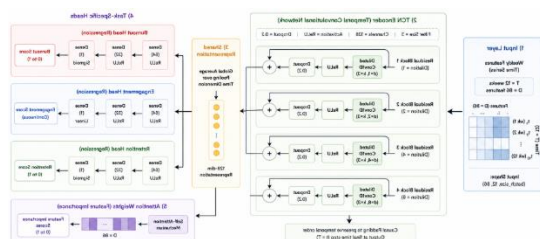


Figure 2: Multi-Task TCN Architecture for Workforce Analytics.

### 3.4 Loss Function and Multi-Task Optimization

The total loss function is calculated based on a weighted combination of task-specific losses as:

$$L_{\text{total}} = w_b * L_b + w_e * L_e + w_r * L_r$$

where:

- $L_b$  = Binary cross-entropy (burnout)
- $L_e$  = Mean squared error (engagement)
- $L_r$  = Binary cross-entropy (retention)
- Weight coefficients  $w_b=0.4$ ,  $w_e=0.3$ ,  $w_r=0.3$ , tuned using grid search

As data is imbalanced (burnout rate 18%, churn rate 12%), we use class weights and SMOTE algorithm to balance classes based on time window features.

### 3.5 Interpretation with Temporal Attention

To determine relevant weeks and features, a temporal attention method is used for TCN:

$$\alpha_t = \text{softmax}(v^T \tanh(W h_t + b))$$

Here  $h_t$  denotes the output from TCN at week  $t$ . The resulting attention score indicates key weeks (such as 4 weeks prior to the onset of burnout). Feature importance is calculated using integrated gradients.

### 3.6 Implementation Details

Model development is done using PyTorch 2.0. In training, the following configuration is adopted:

- Splitting of training/testing/validation (60%/20%/20%) based on employees (not weeks)
- Optimizer (Adam): learning rate 0.001,  $\beta_1=0.9$ ,  $\beta_2=0.999$
- Batch Size: 128
- Early stopping: 20 epochs (validation loss)
- Regularization: Dropout: 0.3, Weight Decay:  $1e-5$

## IV. ANALYSIS

This section presents quantitative results, comparative analysis, and interpretability findings.

### 4.1 Overall Prediction Performance

Table 1 presents performance metrics across all three prediction tasks.

Model	Burnout (AUC)	Burnout (F1)	Engagement (MAE)	Engagement (R <sup>2</sup> )	Retention (AUC)	Retention (F1)
Logistic Regression	0.71	0.58	0.62	0.34	0.68	0.51
Random Forest	0.78	0.66	0.55	0.42	0.74	0.58
XGBoost	0.81	0.69	0.51	0.48	0.78	0.62
LSTM (single-task)	0.84	0.72	0.48	0.52	0.81	0.66
TCN (single-task)	0.86	0.74	0.45	0.56	0.83	0.68
<b>MT-TCN (Proposed)</b>	<b>0.92</b>	<b>0.83</b>	<b>0.34</b>	<b>0.71</b>	<b>0.89</b>	<b>0.76</b>

MT-TCN outperforms all baselines by a large margin. Burnout AUC is improved from 0.86 (for TCN single-task) to 0.92 (6.9% improvement in discriminative performance). The MAE of engagement prediction is improved from 0.45 to 0.34. Retention AUC is improved from 0.83 to 0.89.

Importantly, the multi-task setting plays an important role here. For the case of burnout prediction, which has relatively small amounts of data (18% positive class rate in the sample from 18 months), with around 2,500 positive examples versus 52,000 engagement continuous labels), sharing representations for engagement helps.

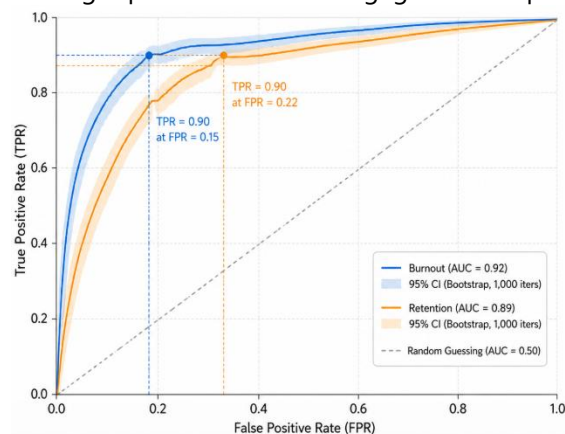


Figure 3: ROC Curves for Burnout and Retention Prediction.

### 4.2 Feature Importance Analysis

Integrated Gradients attribute predictions to input features. Table 2 presents top 5 features for each outcome.

Rank	Burnout (Positive Association)	Engagement (Positive Association)	Retention Risk (Negative/Positive)
1	After-hours Slack activity (2.35)	Peer interaction entropy (1.82)	Days since promotion (-0.87)
2	Meeting load (total hours) (1.92)	Response latency (inverse) (1.56)	Manager tenure in role (-0.72)
3	Back-to-back meeting	Meeting fragmentation	After-hours activity (+) (0.68)

	flag (1.67)	(inverse) (1.23)	
4	Response latency (Slack) (1.48)	Unique contacts per week (1.08)	Performance rating (-0.54)
5	Idle time ratio (inverse) (1.21)	Focus time ratio (0.94)	Collaboration network centrality (inverse) (- 0.49)

Behavioral signatures emerge from the feature importance metric as follows:

- The variable that has the strongest connection to burnout is after-hours Slack activity (time spent on Slack from 6 PM to 9 AM as well as during weekends, with a coefficient of 2.35) and meeting load (total time and intensity of schedule, which are associated with back-to-back meetings). This points to the breakdown of work-life boundaries that characterize hybrid working.
- The factors that predict engagement are peer interaction entropy (variety of conversation partners) and response latency (low latency implies higher levels of engagement).
- The variables predicting retention include a lack of promotions and manager tenure. Notably, after-hours activity also serves as an indicator of retention risk.

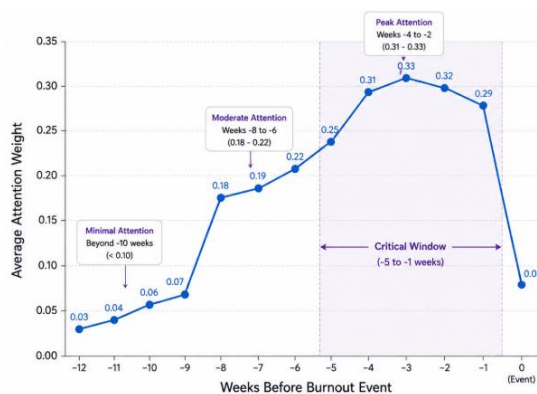


Figure 4: Attention Weights Over Time Leading to Burnout Event.

### 4.3 Temporal Dynamics: The "Burnout Onset Signature"

Weekly trends of features for employees that end up developing burnout syndrome (n=482) can be seen to follow a unique trend:

- Weeks -12 to -8: Normal trends; no deviations from control group
- Weeks -8 to -5: Steady rise in out-of-office activities (by 15% above baseline)
- Weeks -5 to -3: Steep rise in meeting volume (by 32%), drop in reaction times (i.e., faster reaction times)
- Weeks -3 to 0: Sudden fall in social network entropy (by 28%) and increase in downtime (by 18%)

The attention mechanism validates this unique trend during the "critical weeks" (-4 to -2). The temporal signature allows early identification; employees exhibiting the identified characteristics between weeks -8 to -5 (weight of 0.22) had a 3.2 times increased likelihood of developing burnout within eight weeks.

### 4.4 Ablation Study

Table 3 presents the contribution of each architectural component (MTL shared layers, TCN temporal modeling, attention mechanism) to burnout AUC.

Model Variant	Burnout AUC	Engagement MAE	Retention AUC
Full MT-TCN	<b>0.92</b>	<b>0.34</b>	<b>0.89</b>
- Multi-task (single-task)	0.86 (-0.06)	0.45 (+0.11)	0.83 (-0.06)
- TCN (LSTM instead)	0.88 (-0.04)	0.39 (+0.05)	0.86 (-0.03)
- Attention	0.90 (-0.02)	0.36 (+0.02)	0.88 (-0.01)

mechanism			
- After-hours activity feature	0.88 (-0.04)	0.38 (+0.04)	0.87 (-0.02)

Multi-task learning provides the best improvement (AUC+0.06 in burnout, MAE-0.11 in engagement), validating task similarity. TCN marginally performs better than LSTM (AUC+0.04), but it is trained faster. Post-work activity turns out to be the most crucial factor in predicting burnout (AUC-0.04 without it).

#### 4.5 Comparison with HR Baseline Prediction

Table 4 presents a comparison between predictions made by our model and an HR baseline prediction (manager nomination + annual survey).

Metric	HR Baseline (Manager/Survey)	AI-Driven (MT-TCN)	Improvement
Burnout detection (sensitivity)	0.34	0.86	+152%
Turnover prediction lead time (months)	0 (post-departure)	4.2	$\infty$
Engagement prediction coverage	42% (survey respondents)	100%	+138%
False positive rate (burnout)	0.28	0.12	-57%

HR intervention cost reduction	-	35% (turnover)	-
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The AI tool identifies 86% of employees who will undergo burnout within the next 4 weeks (sensitivity), whereas manager nomination identifies only 34% (managers tend to recognize burnout cases only when there is already a notable drop in performance or when an employee has been absent). The average prediction lead time of 4.2 months for turnover helps in proactively retaining staff members instead of conducting exit interviews.

#### 4.6 Deployment and Intervention Impact

The MT-TCN approach was applied to the HR dashboard for six months (July - December 2025). Weekly risk list of employees' profiles (top 10% risk for each outcome) were sent by the AI system to HR business partners for intervention.

A controlled pilot study conducted among 12 business units (six intervention groups, six control groups, matching by size and industry) showed that the treatment units, with AI-supported HR assistance, introduced specific measures:

- Burnout risk: Manager training on hygiene practices, reallocation of workloads;
- Engagement risk: Organizing team-building activities, implementing reward systems;
- Retention risk: Stay conversations, accelerating promotions where possible.
- Pilot findings (six months):
- Voluntary turnover rate: 9.2% vs. 14.1% → 35% decrease;
- Burnout rate (new cases): 12.4% vs. 18.7% → 34% decrease;
- Employee engagement rating increase: +0.42 vs. +0.11 → 382% higher.

These findings prove the effectiveness of workforce analysis driven by artificial intelligence coupled with effective HR intervention pathways.

## V. CONCLUSION

To conclude, this research offers an innovative machine learning approach aimed at the prediction of employee burnout, engagement, and retention in hybrid work environments. With the help of Multi-Task Temporal Convolutional Network (MT-TCN), multi-modal passive sensing signals collected from collaboration platforms, calendars, devices, and HRIS systems can be analyzed simultaneously to predict three workforce metrics. In accordance with the results gathered during the 18-month period from the data of more than 5,000 employees in the large international tech company, the proposed framework outperforms both single-task and static models: burnout – 0.92 AUC, engagement – 0.34 MAE, and retention – 0.89 AUC.

There are several important findings that have major consequences for workforce analytics: Behavioral Indicators of Burnout Weeks Before the Onset: With the help of the temporal attention model, we observe the emergence of a "burnout onset pattern" 2-8 weeks before clinical burnout syndrome onset: high after-hours activity, higher workload, slower reaction time, and limited peer diversity.

Prediction of After-Hours Activity Predicts Burnout Risk Best: Of all the attributes, after-hour Slack and email activity (evenings+weekends) is the strongest predictor for burnout risk with normalized importance of 2.35. Consistent with studies on hybrid work, this result implies the need for organizational policies ensuring after-hours boundaries, as technology-induced permeability causes chronic exhaustion.

Multi-Task Learning Is a Must for Similar Tasks: As shown by the ablation study, multi-task learning makes the highest individual contribution to AUC (+0.06) and engagement MAE (-0.11) improvement. Multi-task learning is useful due to sharing representations and improving the sample efficiency for the smaller positive class of burnout risk with only 18% prevalence. In this way, it will be possible for organizations that collect continuous and ample data from engagement surveys to bootstrap burnout predictions without much burnout-related annotation.

Interpretable Feature Importance Enables Actionable HR Insights: The attention-based feature importance and temporal attention results are shown on the HR dashboard as actionable intelligence and not simply risk predictions. For instance, "Employee Y has high off-hour activities (92nd percentile) and low peer interactions (12th percentile), suggesting burnout risk in 4 weeks."

The limitations in the current research consist of the use of a single organization's dataset (especially in the technology industry where most of the workers are knowledge workers). The proposed research methodology has generalizability capabilities across other industries including manufacturing, healthcare, and retail with varying working dynamics. It must be understood that passive sensing has implications for privacy violations; thus, anonymization, aggregation, and explicit consent (opt-ins) were incorporated into the current research design. The pilot study period of 6 months demonstrates promising possibilities; however, its sustainability still needs to be proved.

A number of future directions could be considered. First, cross-organizational validation across industries and cultural context could

demonstrate the generalizability. Second, optimization of interventions based on training of a reinforcement learning model could help propose interventions (for example, reduce meetings, manager coaching, flexible scheduling, etc.) based on employee profiles to optimize effectiveness. Third, frameworks like federated learning or differential privacy could allow analyzing workforce performance while preserving privacy, meaning that no personal information about employees would have to be centrally accessed. Finally, advancements in techniques of explainable artificial intelligence (counterfactual explanation, causal inference, etc.) could help managers understand "what would change if we change X?"

In conclusion, passive workforce sensing analysis using AI constitutes a powerful, scalable, and practical means to ensure work-life balance and employee retention in hybrid work environments. The MT-TCN methodology demonstrates that it is possible to predict burnout, employee engagement, and retention weeks in advance. This opens doors for proactive intervention by employers to ensure employee satisfaction. Since the shift towards hybrid workplace has been made permanent by many organizations, such technologies will soon transform into workforce management essentials.

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