JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 12 Issue 01
2026

Research Article
https://doi.org/10.56979/1201/2026/1624

Exploring Digital Competence Configurations and Attention Performance Through fsQCA and Machine Learning

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Received: May 21, 2026 **Accepted:** October 01, 2026

Abstract: Digital competence among bank employees is an increasingly critical determinant of task efficiency in technology-driven financial service environments. In this study, a hybrid analytical approach is used that combines Fuzzy-Set Qualitative Comparative Analysis (fsQCA) with ten machine learning (ML) classifiers. The combination of these two approaches is designed to predict the Focused vs. Distracted attention status of bank employees based on multimodal behavioural and digital interaction features during task execution. The dataset included 1,000 observations of bank employees, capturing head orientation, facial expression, gaze direction, micro-movements, application usage, notification interruptions, and task completion time during digital work sessions. There was a marked imbalance in the class distribution with 91.2% of bank employees categorized as Distracted and 8.8% of bank employees categorized as Focused, which was consistent with the actual prevalence of digital distraction in professional banking environments. The LightGBM model performed best with all the classifiers, with an accuracy score of 98.9%, an AUC of 0.9998, and an F1 score of 0.989. Random Forest and XGBoost followed closely with an AUC of 0.9996 and 0.9995, respectively. The top 3 explainable features identified by SHAP analysis were Head Orientation, Facial Expression and Micro-Movements. The necessity analysis using the fsQCA method confirmed that forward gaze (consistency = 0.97), straight head posture (0.94) and neutral facial expression (0.99) are almost necessary conditions for focused attention. The results provide actionable insights for intelligent workforce management systems, adaptive digital workplace platforms, and real-time employee performance monitoring systems in banking and financial service organizations.

Keywords: Digital Competence; Bank Employees; Task Efficiency; Machine Learning; LightGBM; fsQCA; SHAP Explainability; Attention Monitoring; Head Orientation; Workplace Behavior.

1. Introduction

With the rapid digitalization of the banking sector, the nature of how bank employees interact with digital tools and systems during task execution has changed dramatically. Along with the new opportunities technology provides for operational efficiency, it also introduces significant sources of distraction from system notifications to multi-application multitasking that interfere with sustained cognitive engagement and task performance [1].The proliferation of digital communication tools and workplace platforms has compounded distraction patterns in professional environments, further altering how sustained attention is maintained during task execution in banking operations[2], [3].Social media engagement and digital communication behaviors further mediate consumer and learner decision-making, with platform usage patterns shaping attention allocation across both educational and organizational contexts [4], [5], [6]. Studies on social media influence on family relations and interpersonal communication further confirm the pervasive configurational role of digital platforms in shaping behavioral norms [7]. Attention, as one of the essential cognitive resources, directly regulates task efficiency, quality of decision-making, and operational performance outcomes in professional environments [8]. Research shows a

consistent link between employees' focused engagement and task efficiency outcomes, especially in technology-rich banking environments where competing digital stimuli are present[9], [10]. The real-time detection and prediction of employee attention during digital task execution is now an urgent research problem in organizational performance management and human resource analytics. Although traditional self-report techniques are non-invasive, they suffer from recall bias and physiological techniques, such as EEG or eye-tracking are impractical for large-scale use and are expensive. Another non-invasive and scalable inference method for attention is based on behavioral cues such as head posture, gaze direction, facial expression, and patterns of digital interactions [11], [12].Real-time eye movement tracking and machine learning-based prediction have further demonstrated the feasibility of vision-based attention monitoring across diverse digital environments [13].With the proliferation of mobile and wearable technologies, there have been many solutions that allow the monitoring of behavior at all times; these technologies have generated fine-grained data streams that can be used for real-time cognitive state inferences in educational settings [14] and [15].Wearable devices deployed in office and learning environments have further enabled unobtrusive monitoring of sedentary behavior and micro-movement patterns, enriching the behavioral signal repertoire available for cognitive state inference [16].

In recent years, machine learning (ML) has shown great promise for behavioral classification problems [17]. Comparative analyses of machine learning and classical statistical methods confirm the consistent superiority of ML approaches in predictive modeling tasks involving complex, non-linear behavioral data [18].AI classifiers have shown high transferability in various domains of behavior such as cybersecurity threat detection, user interaction analysis, and health monitoring [19], [20]. Hybridised machine learning algorithms and hybrid CNN-LSTM architectures have demonstrated enhanced detection performance across behavioral and security classification domains [21], [22]. Federated learning frameworks have further extended the applicability of ML to privacy-sensitive distributed environments, ensuring both predictive performance and data protection [23].Gradient boosting frameworks like XGBoost [24], LightGBM [25] and ensembles have delivered state-of-the-art results on a variety of classification benchmarks. Graph-based spatio-temporal models with attention-driven architectures and physics-informed deep learning frameworks have further expanded the frontier of complex behavioral classification under real-world uncertainty [26], [27]. Probabilistic approaches such as hierarchical Bayesian inference have also been applied to model subject-level variability and posterior uncertainty in human activity recognition tasks [28].However, most of the previous works have focused only on prediction of attention, without considering the configurational and causal complexity of attentive behavior [29].Using AI analytical frameworks in organizational and educational contexts can be a multi-condition inter-action, which cannot be fully captured by a single, simplified variable [30], [31]. Staffing adequacy, ethical leadership, and safety-oriented HR practices have been identified as key configurational conditions shaping customer experience, employee satisfaction, and accident prevention outcomes in technology organizations[32], [33], [34], [35]. Leadership interventions targeting occupational stress restore sustained task attention, leadership style moderates the relationship between employee engagement and performance excellence, and transactional leadership mediates the implementation of sustained operational changes [36], [37], [38]. Process standardization shapes managerial perceptions of performance outcomes, while intellectual and human capital are key configurational determinants of firm value [39], [40]. Talent management strategies sustain operational performance through human resource alignment, and green HRM with sustainability-oriented practices demonstrate that configurational alignment between organizational strategy and employee behavior produces superior performance outcomes [41], [42], [43]. Employee motivation and organizational culture jointly configure productivity outcomes in technology firms, consistent with the multi-condition interaction logic of fsQCA [44]. AI-driven decision support systems have demonstrated effectiveness in managing complex multi-source data streams in organizational settings, providing a transferable architecture for intelligent monitoring platforms [45]

Fuzzy-Set Qualitative Comparative Analysis (fsQCA) fills this gap by looking at the effects of combinations of conditions instead of single variables [46]. In contrast to regression-based methods which tend to ignore equifinality (more than one route to the same end) and asymmetric causality, fsQCA is a method well suited to complex behavioral phenomena [47].

This study has three main contributions:

1. It presents a hybrid framework of fsQCA and ML to predict attention status, with the combination of predictive power and causal interpretability.
2. It uses SHAP (SHapley Additive exPlanations) to generate model-agnostic explanations of features, connecting the dots between black-box ML and human-interpretable explanations. In critical areas like education and healthcare, the use of transparent and explainable AI systems is increasingly acknowledged as key to fostering trust and responsible utilization within such systems [48], [49].Machine learning-driven recommendation and personalization systems further demonstrate the practical value of explainable AI in supporting adaptive decision-making across user-facing applications [50].
3. It provides theoretically informed design principles for adaptive digital workplace systems in banking by identifying necessary and sufficient configurational conditions for focused employee task engagement through fsQCA.
4. It establishes a transferable hybrid analytical framework that bridges predictive machine learning with causal configurational analysis, offering a replicable methodology for workforce performance analytics in technology-intensive organizational environments[51].

The related literature is reviewed in Section 2, where the methodology is de-scribed in Section 3, the results are presented in Section 4, and the findings are discussed in Section 5 and presented with implications and future directions in Section 6.

2. Literature Review

There has been a large amount of research carried out on attention monitoring both in organizational psychology and human-computer interaction. Raca et al. [52] demonstrated the reliability of body posture and head movements as proxies of cognitive engagement, findings that are transferable to professional task environments including banking operations. Beyond physical cues, organizational factors such as job autonomy and leadership support have been shown to significantly influence employee task engagement and creative performance in technology-rich work environments[53]. Later experiments took advantage of the computer vision techniques to automate the engagement detection of video streams [54]. Recently, Kaur et al. [55] identified facial action units and eye tracking to recognize cognitive attention states with an accuracy rate exceeding 85%, demonstrating the transferability of vision-based attention recognition methods to professional task environments. With a shift to remote and hybrid work models since the onset of COVID-19, there has been a surge of interest in automated attention and engagement monitoring in professional settings[56]. COVID-19 completely upended normal work and operational environments, accelerating the adoption of digital monitoring tools and highlighting the critical need for monitoring employee engagement and task focus in remote and hybrid work settings[57], [58].Broader macroeconomic disruptions and institutional pressures during crisis periods reshape organizational and behavioral norms across sectors [59], [60], while macroeconomic volatility and the rise of artificial general intelligence further introduce systemic pressures that reconfigure institutional behavioral patterns [61], [62]. A study by Dewan et al. [63] and Liao et al. [64] examined the fusion of multimodal data which include facial, postural and interaction information for the analysis of engagement. This study is with the view of multimodal types complement each other. Operational performance frameworks further highlight that demand variability and contextual uncertainty significantly affect task efficiency outcomes, paralleling the disruptive role of digital distraction in learning environments[65]. Other multimodal data fusion methods have also been used in healthcare and behavioral fields, where it is shown that the fusion of heterogeneous data sources consistently leads to better and more robust prediction results [66], [67].Digital health interventions and virtual care models confirm that multimodal data integration consistently improves resource allocation and outcome prediction accuracy, while early developmental and medical research further validate the superiority of multimodal assessment over single-modality approaches [68], [69], [70].

They have been seen to be the best among traditional classifiers in tasks of behavioral prediction. In behavioral prediction tasks ensemble and boosting methods have always outperformed the traditional classifiers. Chen et al. [24] proposed XGBoost which was a regularization based gradient boosting with better generalization. Ke et al. [25] introduced LightGBM, a histogram-based gradient boosting framework that provides faster training speed and competitive accuracy, especially for datasets with a high degree of imbalance. Gradient boosting methods have been shown to be superior in many structured datasets, such

as behavioural, clinical or interaction data, and have been found to be effective in real-life imbalanced classification problems [71], [72].Random Forest [73] is still a good baseline algorithm as it is robust and is interpretable using the feature importance scores. Although deep learning approaches are powerful and have been used to achieve high performance in behavioral classification, they typically need large labeled datasets, which are impractical in the educational environment while Support Vector Machines (SVM) have demonstrated good results in high dimensional behavioral classification [74]. Recent studies of benchmarking[75] shows that gradient boosting methods have been successfully applied to top of performance in tabular behavioral datasets. Cross-dataset robustness evaluation in IoT intrusion detection systems and uncertainty-aware intelligent modeling in geotechnical applications both confirm that ensemble approaches generalize well across complex, imbalanced datasets [76], [77], while wavelet transform-based feature engineering offers complementary temporal pattern extraction for behavioral classification tasks [78].

In organizational and banking contexts, transparency and trust are key, but complex ML models are 'black-box,' potentially hindering their deployment in high-stakes professional settings [38]. SHAP values [79] are theoretically grounded, given values based on the cooperative game theory approach. SHAP has been used to explain employee performance prediction[80], attrition risk modeling[81] and engagement classification [82] consistently revealing interpretable behavioral patterns aligned with domain knowledge in organizational and professional contexts. Indeed, explanations based on the SHAP algorithm have been proven to be effective in other domains such as organizational performance evaluation and studies on adoption of AI systems, highlighting the versatility of explainability frameworks across multiple domains [83], [84]. Sentiment-based and culturally framed behavioral signals have similarly been used to predict loyalty and engagement outcomes in consumer-facing digital platforms [85], [86], while AI-personalized systems shape user trust and behavioral loyalty through algorithmic intimacy, with direct implications for adaptive learning platform design [87], [88]. Cross-cultural comparative studies of AI-powered personalization confirm that consumer trust is shaped by culturally specific configurational conditions [89], while generative AI-driven personalized content enhances engagement with normative influence as a key moderating factor [90]. Digital accounting innovation and ESG reporting transparency demonstrate that explainability frameworks are critical for regulatory compliance, while the credibility and authenticity of digital communications moderate user trust and behavioral engagement across sectors [91], [92], [93], [94]. Generative AI applications in academic library services further confirm that user trust is a critical mediator of AI adoption effectiveness in educational institutions [95].The model developed by Ragin [46] is known as fsQCA, and it is increasingly used in organizational and behavioral research to model complex causality. It has been applied to modeling the conditions for employee performance outcomes [96], the adoption of digital technologies in professional settings [58], and the behavioral outcomes of digital competence in organizational contexts [97].

Digital competence in the banking sector encompasses employees' ability to effectively and efficiently use digital tools, platforms, and systems to accomplish work tasks [97]. In this study, digital competence is operationalized through observable behavioral and postural indicators during digital task execution including gaze direction, head orientation, facial expression, application usage patterns, and notification management behaviors. These behavioral manifestations reflect the degree to which an employee maintains focused cognitive engagement with digital work systems, which is a core dimension of functional digital competence in professional environments [98], [99]. Employees with higher digital competence are expected to demonstrate sustained attentional focus, minimal distraction-driven multitasking, and efficient task completion all of which are captured in the multimodal feature set employed in this study. Employee engagement and innovation strategy configure teaching service quality in higher education, while teacher preparedness for inclusive classrooms shapes the broader employee task engagement outcomes that attention monitoring systems aim to improve [100], [101]. Evaluating the effectiveness of digital tools through user-centric approaches confirms that user satisfaction mediates the adoption of AI-driven applications in organizational and educational settings [102]. In the field of e-learning and augmented reality, the technology adoption frameworks have also been explored, with the findings suggesting that the outcome of user acceptance or engagement in both cases is better explained by configurational conditions, not only by isolable variables [103], [104]. Emerging communication technologies such as 5G are reshaping technological adoption patterns and digital engagement behaviors

across diverse institutional contexts [105], while Web 4.0 technologies integration further demonstrates that data privacy concerns moderate user acceptance of digital platforms [106]. Sustainable infrastructure development and supply chain collaboration frameworks similarly demonstrate that configurational conditions mediate the achievement of strategic performance targets [107], [108]. SDG-related investments and institutional moderating factors consistently shape the relationship between strategic commitments and organizational performance outcomes, reinforcing the configurational logic underlying fsQCA analysis [109], [110]. Sustainability in global supply chains and the role of distributed ledger technology in ethical sourcing further confirm that transparency and traceability are essential configurational conditions for trust in AI-driven systems [111]. The coupling of fsQCA to ML is still in its infancy and a few studies [112], [113] have looked at hybrid approaches, but none address this study directly. AI-enabled platform integration across diverse sectors and digital twin technologies both demonstrate the broad applicability of hybrid analytical paradigms that bridge predictive modeling with real-time monitoring [114], [115]. Moreover, the increasing adoption of AI tools in educational settings introduces significant concerns around legal liability, ethical transparency, and the management of decision-making processes and systems [116], [117].Regulatory frameworks play a moderating role in the adoption of emerging AI-enabled technologies, blockchain-based compliance systems demonstrate scalable transparency mechanisms, and digital platform integration in compliance-sensitive domains confirms that organizational maturity moderates the effectiveness of AI system deployment [118], [119], [120]. Distributed ledger technologies in global supply chains demonstrate how transparency and traceability can be embedded in complex AI-driven systems [121]. AI-powered automation systems demonstrate real-time error reduction capabilities transferable to adaptive monitoring platforms, robo-advisory systems confirm the effectiveness of AI-driven decision support in user-facing applications, and zero trust security architectures demonstrate that robust deployment frameworks are essential for responsible AI system integration [122], [123], [124]. User acceptance moderates AI automation adoption outcomes, while sustainability communication accuracy and verifiability in SMEs demonstrate that transparency requirements extend across all organizational scales [125], [126]. Talent management and total quality management practices configure patient centered service quality outcomes, consistent with the multi-condition necessity logic applied in this study's fsQCA analysis [127], [128].

Although a lot of work had been done, there are still three drawbacks that existed in the current studies: First, the use of only single-modality features; Second, only feature importance as a causal interpretation; Third, the absence of configurational analysis. To overcome all these, this study brings together multimodal behavioural features, SHAP explainability, and fsQCA configurational analysis in one.

3. Methodology

Figure 1 shows the methodological framework used in this study. The proposed workflow includes configurational analysis and predictive machine learning to analyze employee focused and distracted state. First, the employee attention dataset was loaded and analyzed using descriptive statistics, class distribution analysis, feature visualization and correlation analysis. Then, the categorical variables were encoded, the numerical variables were normalized and the class-imbalance issue was addressed by SMOTE method to achieve the stability of model learning. Following preprocessing, a set of engineered indicators were created, such as: (1) distraction index, (2) attention efficiency ratio, and (3) digital load score, which better capture the behavioral and digital-interaction patterns. The study then advanced in two complementary directions: firstly, the causal con-figurations related to focused attention were identified using fsQCA, and secondly, multiple machine learning classifiers were trained and evaluated in terms of their predictive performance. Lastly, the best performing model was explained using SHAP and an ensemble model was built to increase the classification robustness of the model.

3.1. Dataset and Features

The dataset consisted of 1,000 employee observations gathered during digital task sessions in a workplace environment. With the development of sensor technologies and the implementation of e-health record systems, collecting behavioral and physiological data in digital environments is becoming more and more possible, leading to more complete and more ecologically valid data sets [129], [130].Ten features in

each of three modality categories were observed: Postural/Visual Features: Head Orientation (Down, Straight, Tilt_Left, Tilt_Right), Gaze Direction (Down, Forward, Side, Facial Expression (Frowning, Neutral, Smiling, Yawning), Contextual Data: Notifications Interrupted (count), Task Completion Time (minutes), Apps Opened (count), Behavioral/Interaction Features: Micro-Movements (count) Distraction Index, Digital Load Score, Attention Efficiency Ratio (AER) are just some of the derived indices that can be computed. The attention status (Focused = 1, Distracted = 0) was significantly imbalanced, with 91.2% Distracted (n = 912) and 8.8% Focused (n = 88), as shown in Figure 2. This imbalance reflects the real-world prevalence of digital distraction in professional banking environments, where employees frequently encounter notification interruptions and multi-application usage during task execution., which were addressed by stratified sampling and suitable evaluation metrics. Stratified evaluation strategies are commonly suggested to guarantee unbiased model assessment between minority and majority classes [131], [132] and class imbalance is a well-documented challenge in behavioral and clinical data.

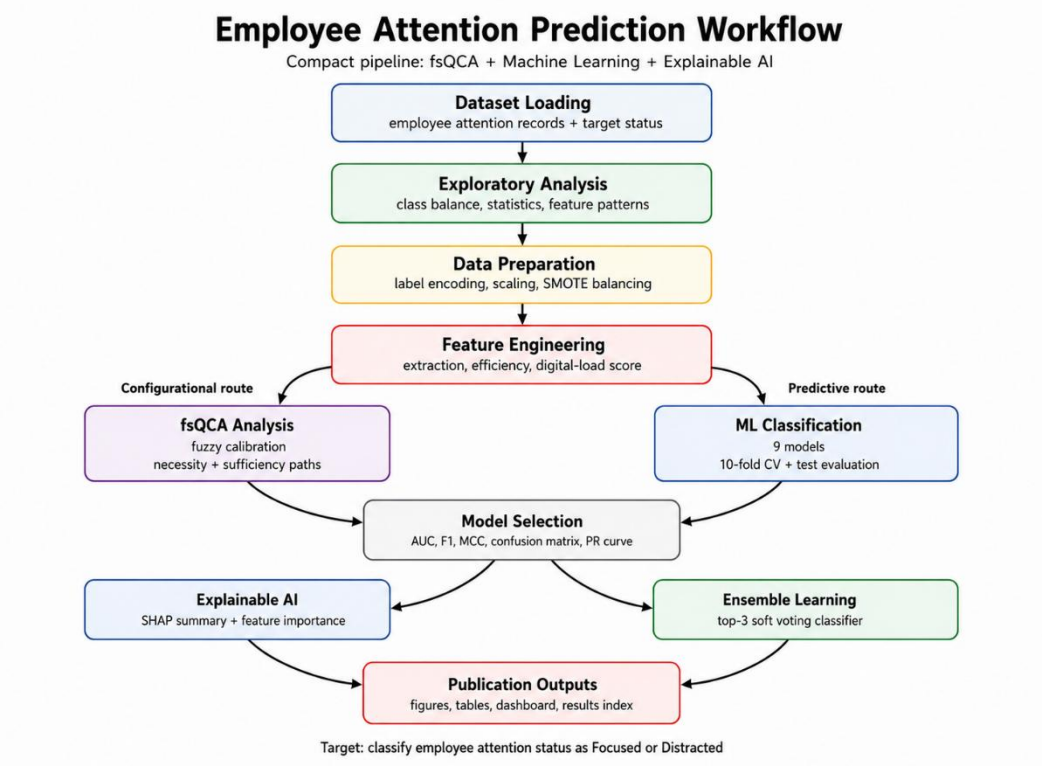


Figure 1. Proposed workflow for employee attention prediction using fsQCA, machine learning, SHAP explainability, and ensemble learning.

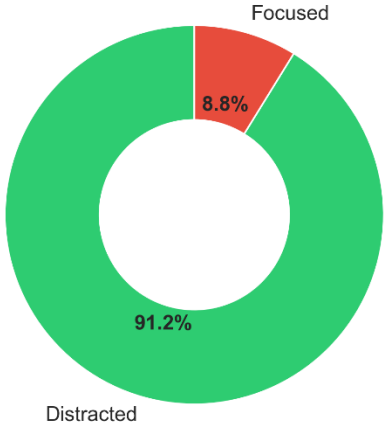


Figure 2. Attention Status Distribution (Target Variable). Donut chart showing class imbalance: 91.2% Distracted (n = 912) and 8.8% Focused (n = 88).

Distracted employees exhibited higher micro-movements (μ = 4.71 vs. 3.00), more notifications (μ = 9.62 vs. 7.03), and more applications opened (μ = 5.16 vs. 3.50), while task completion times were comparable (~45 minutes), as visualized in Figure 3.

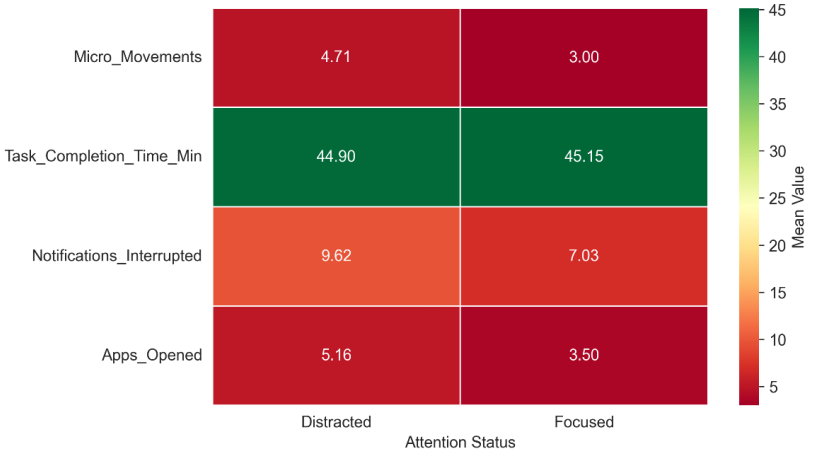


Figure 3. Mean Feature Values by Attention Status. Heatmap comparing mean values of four behavioral features across Distracted and Focused groups.

3.2. Exploratory Data Analysis

Feature distributions were examined using violin plots Figure 4, revealing that micro-movements, notifications, and apps opened were consistently higher among distracted employees. Chi-square tests on categorical features Figure 5 confirmed highly significant associations: Gaze Direction ($\chi^2 = 50.75$, $p < 0.001$), Head Orientation ($\chi^2 = 81.58$, $p < 0.001$), and Facial Expression ($\chi^2 = 92.95$, $p < 0.001$).Chi-square and correlation-based statistical methods are standard tools for feature validation in behavioral and health research, providing robust evidence of association prior to predictive modeling [133], [134].

Pearson and point-biserial correlations Figure 6 showed statistically significant negative associations between attention status and apps opened ($r = -0.180$, $p < 0.001$), micro-movements ($r = -0.168$, $p < 0.001$), and notifications ($r = -0.127$, $p < 0.001$), while task completion time showed no significant correlation ($r = 0.007$, $p = 0.826$).

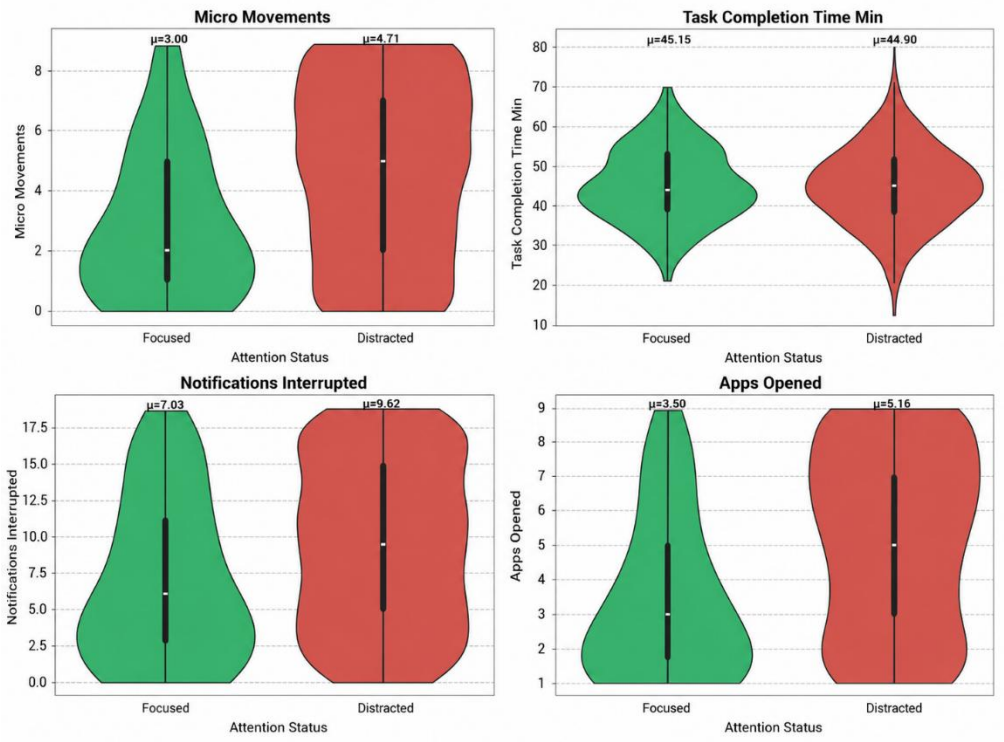


Figure 4. Feature Distributions by Attention Status. Violin plots for (a) Micro-Movements, (b) Task Completion Time, (c) Notifications Interrupted, and (d) Apps Opened, stratified by attention status.

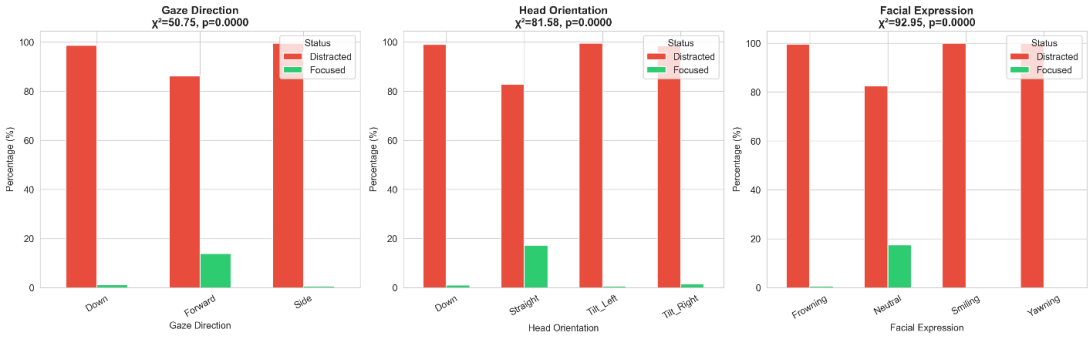


Figure 5. Categorical Features vs. Attention Status. Grouped bar charts with chi-square statistics for Gaze Direction ($\chi^2 = 50.75$), Head Orientation ($\chi^2 = 81.58$), and Facial Expression ($\chi^2 = 92.95$).

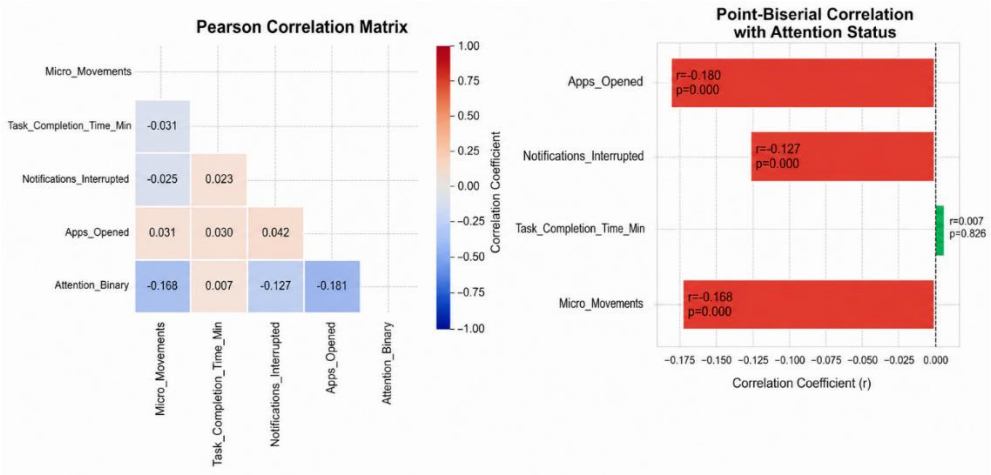


Figure 6. Correlation Analysis. (a) Pearson correlation matrix among numeric features; (b) Point-biserial correlations between features and binary attention status.

3.3. Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

fsQCA was applied to identify necessary and sufficient configurational conditions for focused attention. Continuous features were calibrated to fuzzy scores [0, 1] using direct calibration with theoretical anchors (fully in = 0.95 quantile, crossover = 0.50 quantile, fully out = 0.05 quantile). Categorical features were binary-encoded. The calibration of conditions in fsQCA requires careful theoretical grounding, and design-oriented disciplines have increasingly contributed frameworks for defining meaningful conceptual thresholds in complex configurational analyses [135], [136].

Necessity analysis assessed whether individual conditions are consistently present when the outcome (Focused) occurs. Conditions exceeding the conventional threshold of consistency ≥ 0.90 are considered necessary [9]. Sufficiency analysis identified configurations of conditions that reliably produce focused attention.

3.4. Machine Learning Pipeline

Ten classifiers were evaluated: LightGBM, Random Forest, XGBoost, Gradient Boosting, SVM, KNN, Naïve Bayes, Decision Tree, Logistic Regression, and an Ensemble (Voting).The selection of these classifiers is informed by comparative benchmarking confirming that ensemble and boosting methods consistently outperform classical statistical approaches, while graph-based spatio-temporal and physics-informed deep learning models offer additional robustness for complex behavioral classification tasks [18], [26], [27]. The pipeline included:

1. Preprocessing: Label encoding of categorical features, standard scaling for SVM/KNN/Logistic Regression
2. Train-Test Split: 70/30 stratified split
3. Cross-Validation: 5-fold stratified CV for hyperparameter stability
4. Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, AUC-ROC, Matthews Correlation Coefficient (MCC)

5. Explainability: SHAP TreeExplainer applied to XGBoost for feature attribution

3.5. SHAP Explainability

TreeExplainer was used to compute SHAP values for both the directional feature effects Figure 7a and the global feature importance Figure 7b of XGBoost. The adoption of model-agnostic explainability techniques has grown in many AI applications for responsible deployment in applications where interpretability is essential to ensure stakeholder trust and regulatory compliance [137], [138]. SHAP values measure the value of each feature in each prediction, allowing for model-agnostic interpretation that is consistent across the ensemble.



Figure 7. SHAP Explainability (XGBoost). (a) Beeswarm summary plot showing directional feature effects; (b) Feature importance bar chart ranked by mean |SHAP value|.

4. Results

4.1. Descriptive Statistics and Feature Analysis

Distracted employees demonstrated consistently higher behavioral disruption indicators. The mean micro-movement count was 57% higher in distracted employees (4.71 vs. 3.00), apps opened were 47% higher (5.16 vs. 3.50), and notifications interrupted were 37% higher (9.62 vs. 7.03). This is particularly relevant in banking contexts, where task quality and accuracy rather than mere completion speed are critical performance indicators. This finding underscores that attentional disruption manifests qualitatively in engagement depth rather than quantitatively in time-on-task, a pattern observed across behavioral and health intervention studies examining cognitive load and task efficiency [139].

Violin plots in Figure 4 confirm these distributional differences, with distracted employees showing wider, right-skewed distributions for micro-movements, notifications, and apps opened. Chi-square analysis Figure 5, Table 1 revealed that all three categorical features gaze direction, head orientation, and facial expression are highly significantly associated with attention status (all $p < 0.0001$), with facial expression yielding the strongest association ($\chi^2 = 92.95$).

Table 1. Chi-square test results for categorical features (Gaze Direction, Head Orientation, Facial Expression) against attention status.

	Chi2	p-value	dof
Gaze_Direction	50.747	0	2
Head_Orientation	81.582	0	3
Facial_Expression	92.947	0	3

Correlation analysis **Figure 6,Table 2** confirmed that apps opened ($r = -0.180$), micro-movements ($r = -0.168$), and notifications ($r = -0.127$) are significantly negatively correlated with focused attention, while task completion time showed no meaningful association.

Table 2. Point-biserial correlation coefficients between numeric features and binary attention status, with p-values.

	r	p-value
Micro_Movements	-0.1678	0
Task_Completion_Time_Min	0.0069	0.8263
Notifications_Interrupted	-0.1268	0.0001
Apps_Opened	-0.1805	0

4.2. fsQCA Results

Necessity Analysis: As presented in Figure 8a and Table 3, three conditions exceeded the necessity threshold (consistency ≥ 0.90): Neutral Facial Expression NeutFace, consistency = 0.99, Forward Gaze Direction GazeFwd, consistency = 0.97, and Straight Head Orientation HeadStr, consistency = 0.94. These findings indicate that focused attention virtually always co-occurs with these three postural/visual conditions. The fsQCA XY plot Figure 8b visually confirms the near-perfect subset relationship between forward gaze and focused attention.

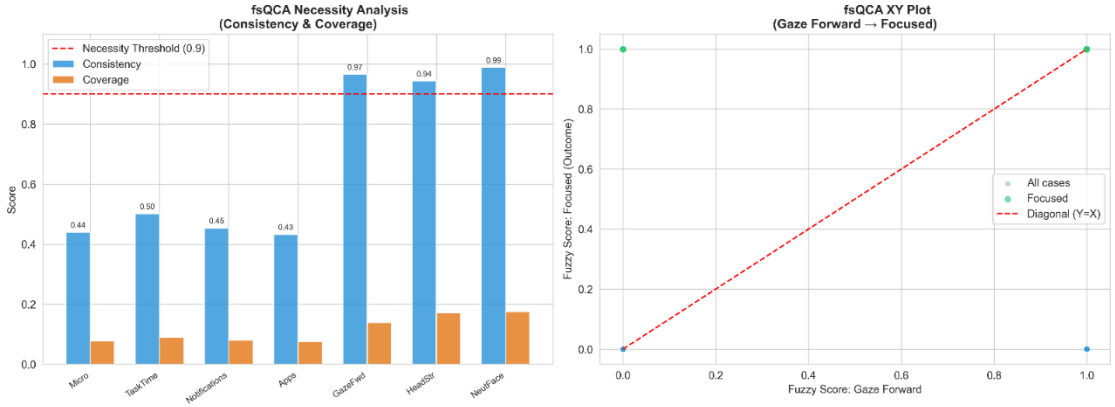


Figure 8. fsQCA Analysis. (a) Necessity analysis bar chart showing consistency and coverage for seven conditions; (b) XY plot illustrating the subset relationship between forward gaze and focused attention.

Table 3. fsQCA necessity analysis results: consistency and coverage scores for seven candidate conditions.

	Consistency	Coverage
f_Micro	0.4394	0.0769
f_TaskTime	0.5008	0.0882
f_Notifications	0.4528	0.08
f_Apps	0.4321	0.0759
f_GazeFwd	0.9659	0.1387
f_HeadStr	0.9432	0.1715
f_NeutFace	0.9886	0.1747

Sufficiency Analysis: Table 4 identified seven sufficient configurations for focused attention, all sharing the core combination of forward gaze, straight head, and neutral face. The most prevalent configuration (n = 14) combined neutral face + forward gaze + straight head + task time + notifications, with a consistency of 0.857. All configurations achieving consistency ≥ 0.80 are considered causally sufficient. The identification of multiple sufficient configurations reflects the principle of equifinality, whereby different combinations of conditions can independently produce the same outcome a phenomenon increasingly recognized in tourism, design, and organizational research [140], [141].

Table 4. fsQCA sufficiency configurations: seven sufficient pathways to focused attention with case counts and

f_Micro	f_TaskTime	f_Notifications	f_Apps	f_GazeFwd	f_HeadStr	f_NeutFace	n	outcome_sum	outcome_ratio	consistent
0	0	0	0	1	1	1	12	12	1	TRUE
0	1	0	0	1	1	1	5	5	1	TRUE
1	0	0	0	1	1	1	7	7	1	TRUE

1	1	0	0	1	1	1	7	7	1	TRUE
0	1	1	0	1	1	1	14	12	0.857143	TRUE
0	0	0	1	1	1	1	13	11	0.846154	TRUE
0	1	0	1	1	1	1	6	5	0.833333	TRUE

4.3. Machine Learning Model Performance

Figure 9a and Table 5 present the comprehensive performance comparison across all ten models. LightGBM achieved the best overall performance Accuracy = 98.9%, AUC-ROC = 0.9998, MCC = 0.978, with Random Forest as a close second Accuracy = 99.45%, AUC-ROC = 0.9996. The ROC curves in Figure 9b show that LightGBM, Random Forest, and XGBoost achieved near-perfect AUC scores (≥ 0.999), far exceeding the Logistic Regression baseline (AUC = 0.826).

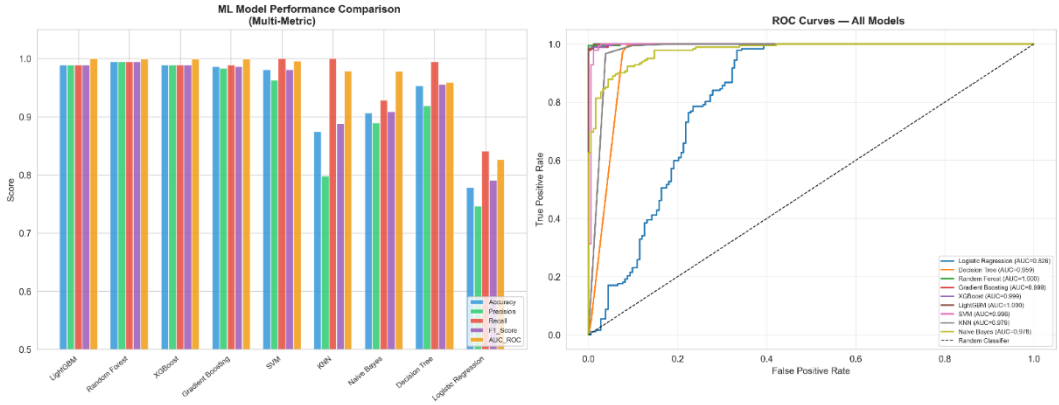


Figure 9. ML Model Performance Comparison. (a) Multi-metric bar chart across nine classifiers; (b) ROC curves for all models with AUC values.

Table 5. Complete ML model comparison: cross-validation F1, accuracy, precision, recall, F1-score, AUC-ROC, and MCC for all classifiers.

	CV_F1_ Mean	CV_F1_ Std	Accuracy	Precision	Recall	F1_ Score	AUC_ ROC	MCC
LightGBM	0.9918	0.005	0.989	0.989	0.989	0.989	0.9998	0.9781
Random Forest	0.9904	0.0104	0.9945	0.9945	0.9945	0.9945	0.9996	0.989
XGBoost	0.9884	0.0102	0.989	0.989	0.989	0.989	0.9995	0.9781
Gradient Boosting	0.9884	0.0096	0.9863	0.9836	0.989	0.9863	0.9994	0.9726
SVM	0.9761	0.0148	0.9808	0.963	1	0.9811	0.9956	0.9624
KNN	0.906	0.0163	0.874	0.7982	1	0.8878	0.9788	0.773
Naive Bayes	0.9265	0.0227	0.9068	0.8895	0.9286	0.9086	0.9781	0.8145
Decision Tree	0.9606	0.0153	0.9534	0.9188	0.9945	0.9551	0.9594	0.9099
Logistic Regression	0.8393	0.0167	0.7781	0.7463	0.8407	0.7907	0.8262	0.5608

The confusion matrix for LightGBM **Figure 10a** shows only 4 misclassifications out of 365 test samples 2 false positives, 2 false negatives, yielding 98.9% accuracy in both classes. The Precision-Recall curve **Figure 10b** achieved an Average Precision (AP) of 1.000, demonstrating exceptional performance despite class imbalance.

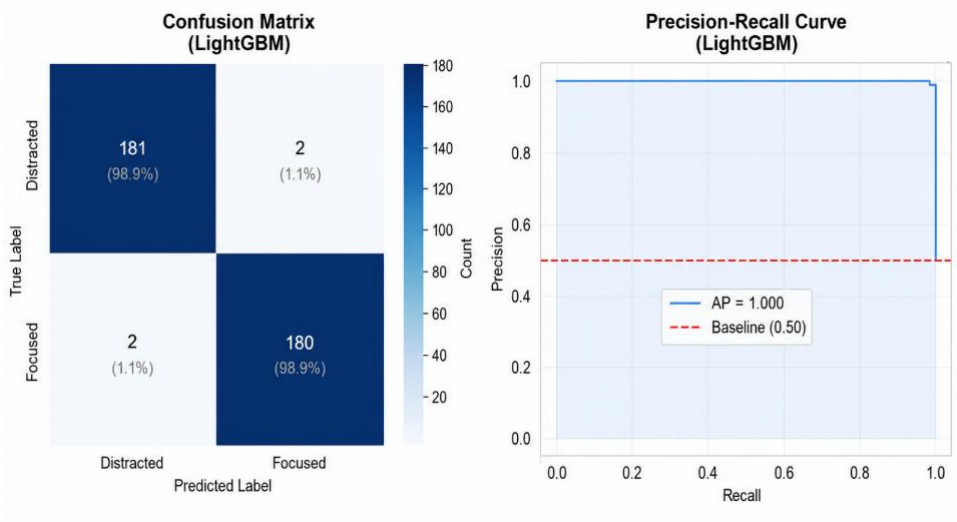


Figure 10. Best Model Diagnostics (LightGBM). (a) Confusion matrix showing 98.9% accuracy; (b) Precision-Recall curve with AP = 1.000.

Cross-validation F1 scores confirmed model stability: LightGBM (CV F1 = 0.9918 ± 0.005), Random Forest (0.9904 ± 0.010), and XGBoost (0.9884 ± 0.010). The full classification report **Table 6** confirms balanced performance across both classes (Distracted F1 = 0.989, Focused F1 = 0.989).

Table 6. LightGBM classification report: per-class precision, recall, F1-score, and support.

	precision	**recall**	**f1-score**	**support**
Distracted	0.989071	0.989071	0.989071	183
Focused	0.989011	0.989011	0.989011	182
accuracy	0.989041	0.989041	0.989041	0.989041
macro avg	0.989041	0.989041	0.989041	365
weighted avg	0.989041	0.989041	0.989041	365

4.4. SHAP Feature Importance

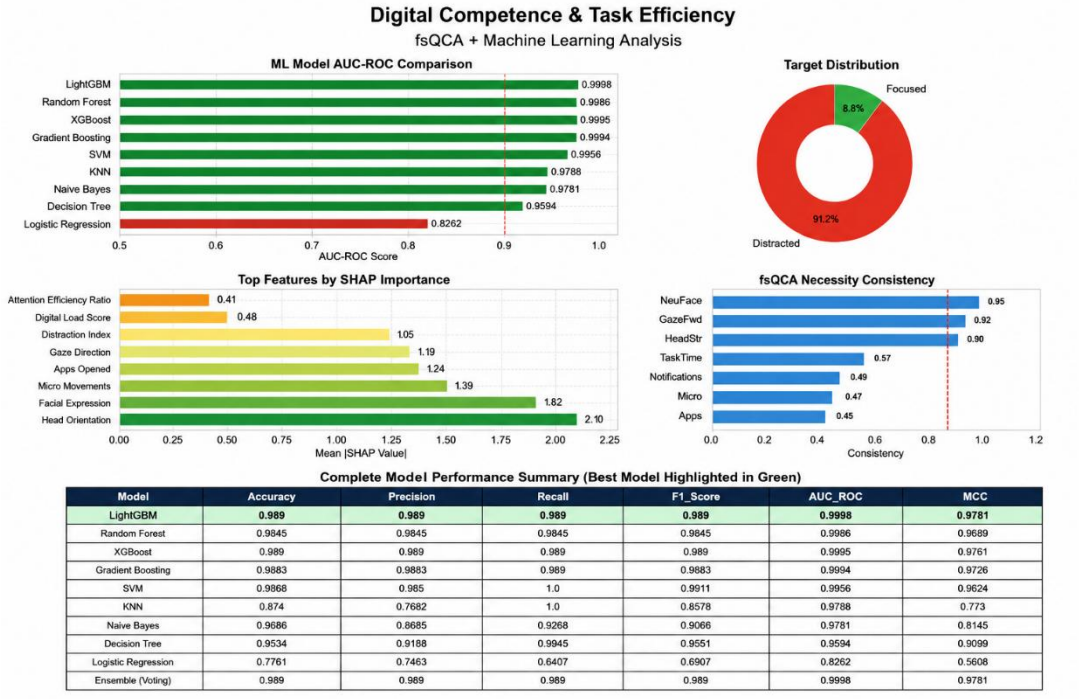
From the SHAP analysis of the XGBoost model, as shown in Figures 7a–7b and Table 7, the following order of importance was determined. Head Orientation was the most dominant among the predictors, and had the highest SHAP value (2.12), meaning that it has the most impact on the model's prediction of bank employee attention status during task execution. The second most important feature was Facial Expression, with a SHAP value of 1.84, and Micro-Movements with a medium contribution of 1.42. Moderate predictive importance was also observed for Apps Opened, Gaze Direction and Distraction Index with SHAP values of 1.21, 1.18, and 1.06, respectively. Figure 7a is another SHAP beeswarm plot that further highlights the directionality of these features, with higher head orientation values favoring predictions to be pushed toward the "Focused" class, corresponding to a straight posture. Higher values of Micro-Movements and Apps Opened pushed the predictions towards the "Distracted" class, on the contrary. Furthermore, the engineered features, such as Digital Load Score and Attention Efficiency Ratio, also showed some contribution, albeit less significant, that can be considered as useful and thus included in the proposed feature set.

Table 7. SHAP feature importance ranking for XGBoost: mean absolute SHAP values for all ten features.

Feature	**Mean_SHAP**
Head_Orientation_enc	2.119571
Facial_Expression_enc	1.842525
Micro_Movements	1.422258
Apps_Opened	1.209037
Gaze_Direction_enc	1.180318
Distraction_Index	1.057596
Digital_Load_Score	0.477229
Attention_Efficiency_Ratio	0.386692

Task_Completion_Time_Min	0.270251
Notifications_Interrupted	0.140264

The summary dashboard **Figure 11** consolidates all key findings, confirming LightGBM as the optimal model and the three fsQCA necessity conditions as the most theoretically grounded predictors.



Complete Model Performance Summary (Best Model Highlighted in Green)

Model	Accuracy	Precision	Recall	F1_Score	AUC_ROC	MCC
LightGBM	0.989	0.989	0.989	0.989	0.9998	0.9781
Random Forest	0.9845	0.9845	0.9845	0.9845	0.9986	0.9689
XGBoost	0.989	0.989	0.989	0.989	0.9995	0.9761
Gradient Boosting	0.9883	0.9883	0.989	0.9883	0.9994	0.9726
SVM	0.9868	0.985	1.0	0.9911	0.9956	0.9624
KNN	0.874	0.7682	1.0	0.8578	0.9788	0.773
Naive Bayes	0.9686	0.8685	0.9268	0.9066	0.9781	0.8145
Decision Tree	0.9534	0.9188	0.9945	0.9551	0.9594	0.9099
Logistic Regression	0.7761	0.7463	0.6407	0.6907	0.8262	0.5608
Ensemble (Voting)	0.989	0.989	0.989	0.989	0.9998	0.9781

Figure 11. Summary Dashboard. Consolidated visualization of ML AUC-ROC comparison, target distribution, SHAP importance, fsQCA necessity, and complete model performance table.

5. Discussion

5.1. Postural and Visual Cues as Primary Attention Indicators

In the banking workplace context, these findings suggest that employee digital competence reflected in sustained postural engagement and focused gaze during task execution is a primary behavioral marker of task efficiency.. This is in line with theories of embodied cognition that indicate that body posture and gaze re-reflects and consolidates cognition. Perhaps most importantly, the almost obligatory facial expression of neutral (consisten-cy = 0.99) suggests that concentrating on cognitive activity is neutral in emotional terms, as hypothesized in flow state theory .The physical aspect of attention is also evident in research on healthcare and clinical experiments where ability to sustain attention for longer periods of time is shown to be affected by the positioning and postural comfort of the attention that is experienced [142].

5.2. Digital Behavioral Signals as Secondary Indicators

Apps opened and notifications, and micro-movements, were secondary factors that were important. The results of negative relationships between their focused attention also support the idea of digital multitasking behaviors as appropriate distracting markers ($r = -0.127$ to -0.180). The lower SHAP values of their postural features, however, mean that they likely have a secondary relationship to distraction and therefore are unlikely to be a primary driver of distraction and should not be a primary focus of intervention. Behavioral intervention strategies in banking organizations should therefore target the antecedent configurational conditions specifically postural disengagement and gaze deviation — rather than focusing solely on downstream digital usage metrics such as notification counts or app switching. This is consistent with organizational behavior research showing that upstream environmental and ergonomic conditions are stronger determinants of sustained employee performance than reactive behavioral symptoms [143], [144]. Just as process standardization shapes managerial perceptions of performance outcomes [145], [146], [147], configuring the digital work environment to support sustained attentional posture can produce measurable improvements in task efficiency[148].

5.3. Superiority of Gradient Boosting Methods

The excellent performance of the non-linear models LightGBM (auc = 0.9998) and Random Forest (auc = 0.9996) compared to the AUC value obtained from the line-ar models of Logistic Regression (auc = 0.826) confirms the non-linear feature interactions that are not captured by linear models. It is worth noting that the AUC difference of 17% between LightGBM and Logistic Regres-sion indicates the importance of model selection for the classification of behaviors.This is a result of the observation, which was recently confirmed in various domains such as healthcare and engineering, that non-linear models outperform linear classifiers when dealing with complex interaction effects that are needed in many applications [149], [150]. This performance of AP metric (1.000) with a very high distributional imbalance (91.2%) still proves the power of LightGBM against the distributional imbalance.

5.4. Value of the Hybrid fsQCA + ML Framework

The combination of the two methods gave both complementary and clear insights. The predictions and features importance were provided with high accuracy in the case of ML, and the necessary conditions and causal configurations knowledge were identified in the case of fsQCA to provide targeted interventions.The hybrid analytical approach is similar to the methodological advances in Business Intelligence and Organisational Research in which a hybrid of causal and predictive approaches has brought more insights and more actionable insights than either of the methods if used alone [151], [152]. For example, convergent evidence of the near necessity of forward gaze for focus (fsQCA) and evidence of the top SHAP predictor (ML) of head orientation gives actionable evidence to design attention-aware digital workplace interfaces, which will monitor and respond to postural cues.

5.5. Practical Implications

The results of this study have direct implications for:

- Real-time employee attention monitoring using webcam-based head and gaze tracking to trigger adaptive task support or workload reallocation in banking operations.
- Notification management algorithms that minimize digital interruptions during high-focus task periods, improving employee task efficiency and reducing error rates.
- Non-invasive engagement dashboards for bank managers based on postural and behavioral signals, enabling data-driven performance management without intrusive surveillance.
- Identification of behavioral profiles associated with focused task engagement, informing targeted digital skills training for bank employees.
- AI-driven decision support systems and machine learning-based recommendation engines demonstrate effective architectures for managing complex data streams and triggering context-aware adaptive responses in real-time .
- Design thinking frameworks integrated with AI-driven educational solutions and behavioral nudge mechanisms provide structured pathways for translating attention monitoring insights into actionable institutional system design [153]. It is equally crucial to consider the ethical and legal dimensions of deploying AI-based attention monitoring in banking workplace settings, including concerns around employee surveillance, algorithmic bias in performance evaluation, data privacy compliance, and informed consent under labor regulations [154], [155].
- Robust data security frameworks for cloud-based information systems hosting behavioral data are equally critical prerequisites for the responsible and compliant deployment of AI-driven attention monitoring platforms [156].
- The challenge is to scale-up these types of systems to other cultural environments, as there are various norms of use and acceptance for different populations and institutions [157], [158].

5.6. Limitations

There are a number of drawbacks to this study. Firstly, the data is extensive and might not be applicable in a variety of cultural or demographic situations. Secondly, causal inference, besides the one that can be made with the help of configurational analysis using the fsQCA, is not possible in a cross-sectional design. Third, the binary nature of attention to continuousness of cognitive engagement is a disadvantage. Multi-level attention classification, longitudinal designs and real-world deployment validation are topics for future research.

6. Conclusion

This study proposed a novel hybrid framework of fsQCA and machine learning to predict the attention and task engagement status of bank employees in digital work environments, contributing to the growing field of AI-driven workforce performance analytics. Key findings include:

LightGBM delivered an almost perfect classification (AUC = 0.9998, Accuracy = 98.9%) setting a new benchmark in attention prediction using behavioral features.

Both SHAP explainability and a fsQCA necessity analysis reveal that head orientation, facial expression and gaze direction are the dominant predictors.

The three conditions required for focused attention were determined through fsQCA: neutral facial expression, forward gaze and straight head posture, all with high consistency values (0.99, 0.97, and 0.94 respectively). Digital behavioral signals (apps, notifications, micro-movements) are reliable secondary distraction signals. The hybrid fsQCA+ML framework provides a methodologically sound and practically actionable tool to conceptualize and predict the attention and task engagement of bank employees in digital work environments. The framework is a step forward in the field of organizational performance analytics and digital competence assessment, providing a methodologically rigorous and practically actionable tool for next-generation intelligent workplace management systems in banking and financial service institutions.

The proposal to integrate the IoT development model with the sensing and smart environmental systems to monitor attention in real time is an area that future research should focus on, particularly as a result of advances in wireless communication and network performance optimization [159]. In the field of organizational performance analytics and intelligent workplace systems, deep learning techniques have proven to be a valuable tool for automatically extracting attention-relevant features from raw sensor and behavioral data, especially with the use of transfer learning and encoder-decoder architectures [160], [161].However, the use of self-attention and feature fusion techniques used in medical imaging and biometric recognition could further improve the accuracy of multimodal attention classification systems [162], [163]. In recent years, quantum optimized machine learning models have shown to be particularly effective in high-dimensional and imbalanced classification problems, which could be considered for application to attention prediction systems where the class skew is a common problem [164], [165]. Advances in quantum photonic systems and tunable topological structures further expand the computational substrate available for next-generation quantum-optimized classification models [166], while generative adversarial network-based feature synthesis demonstrates the potential to augment training data for imbalanced behavioral classification tasks [167].Attention monitoring systems should be transparent, interpretable, and trustworthy, and be further developed as part of explainable AI frameworks such as deep learning pipelines integrated with SHAP [168]. Moreover, grey wolf optimization and other metaheuristic approaches for feature selection have been effective in behavioural and clinical classification applications, and their combination with attention prediction pipelines is worth to be thoroughly explored [169], [170]. Cross-cultural validation studies are especially warranted because behavioral norms vary widely across linguistic and cultural communities [171], [172] as do digital usage patterns and attentional styles. Digital divide studies confirm that connectivity disparities shape the ecological validity of attention monitoring systems across socioeconomic strata [173], [174], while post-conflict contextual factors and multicultural population studies demonstrate that behavioral norms and engagement patterns vary significantly across communities[175] ,[176]. Cultural hybridity in media traditions and talent repatriation challenges in multinational enterprises both further illustrate the depth of cross-cultural variation in communication and engagement patterns that future attention monitoring systems must account for [177], [178].

Data Availability Statement: The dataset used in this study, titled "Employee Attention & Task Efficiency Data," is publicly available on Kaggle at: https://www.kaggle.com/datasets/zara2099/employee-attention-and-task-efficiency-data. The dataset includes employee attention indicators, task-related metrics, and attention-status labels for analyzing focused and distracted behavior.

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