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IoT-Integrated Deep Learning Framework for Cognitive Agent Modeling and Self-Confidence Regulation in the Workplace

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Abstract—**This study presents an IoT-driven framework for real-time assessment and enhancement of workplace self-confidence. By integrating physiological (HRV, EDA, EEG, Pupillometry), behavioral (accelerometers), and environmental (noise, lighting, flame, smoke, gas) sensors, the framework monitors five psychological nodes: Motivation, Effort, Social Persuasion, Knowledge, and Performance. Sensor prioritization and mapping to cognitive constructs enable multi-modal data collection, which feeds into deep learning inspired, system dynamics based cognitive model to capture complex, non-linear relationships and temporal dependencies. Unlike conventional supervised deep neural networks trained via gradient descent, learning is realized through temporal error correction and feedback-modulated adaptation. Simulations across varied workplace scenarios show that the IoT-enhanced model achieves faster convergence and higher steady-state values of self-esteem, self-efficacy, and self-concept compared to non-IoT models. This convergence reflects theoretical stability of the simulated cognitive dynamics rather than real world behavioral validation. Results indicate that real-time sensor feedback stabilizes cognitive and motivational states, improving workplace performance and psychological resilience. Although sensor inputs are simulated to approximate real IoT behavior, the framework is designed to be sensor-ready for future empirical deployment. This framework bridges theoretical cognitive modeling and practical sensor-driven analytics, providing a scalable and adaptive solution for dynamic workplace environments.**

Keywords — Internet of Things (IoT), Deep Learning, Self-Confidence Analytics, Cognitive Modeling, Physiological Sensors, Real-Time Monitoring

I. INTRODUCTION

The Internet of Things (IoT) has revolutionized the way people and objects interact, fostering new discoveries, innovations, and intelligent communication between systems. These developments contribute to improving human living standards and optimizing the use of limited natural and technological resources [1], [2], [3]. IoT operates through an ecosystem of interconnected smart systems supported by diverse wireless communication technologies, including Wi-Fi, Zigbee, and Bluetooth, integrated with actuators and sensors [4]. Moreover, IoT devices are designed according to their specific applications, ranging from smartwatches, wearable sensors, and vehicles to industrial machinery and LED lighting systems [5]. These devices are increasingly embedded across various domains, such as healthcare, transportation, industry, and workplace environments, where they enhance automation, monitoring, sensing, and operational intelligence [6].

IoT produces continuous, multimodal sensor streams such as Heart Rate Variability (HRV), Electrodermal Activity (EDA), Electroencephalogram (EEG), accelerometer, and environmental data that enrich algorithmic models [7]. These systems enable closed-loop operation, allowing algorithms to actuate changes or deliver feedback, including lighting, alerts, or nudges, to optimize workspace and outcomes [8]. With edge and fog computing, latency is minimized, supporting near-real-time predictions and interventions in safety-critical scenarios [9]. Self-confidence can be treated as a dynamic target combining self-efficacy, self-esteem, and performance, which models infer from sensor inputs [10]. By incorporating sensor-driven modulation, deep learning models continuously adapt to internal and external stimuli, improving prediction accuracy [11].

Earlier studies created agent-based simulations to represent self-confidence using theoretical psychological constructs but lacked real-world sensory integration [12], [13], [14]. Although this limitation restricted dynamic adaptability and empirical validation, integrating sensor-based technologies already widely accepted and feasible offers a promising solution to enhance model performance [15]. The newly developed IoT-driven system bridges this gap by incorporating wearable physiological sensors and environmental sensors, allowing real-time data collection to support deep learning–based assessment of self-confidence [16].

The main objective is to advance workplace cognitive modeling by combining IoT sensors with deep learning techniques to more accurately assess self-confidence analytics. Specifically, this research integrates physiological, behavioral, and environmental inputs from IoT-enabled wearable and smartphone sensors to assess cognitive states such as self-esteem, supporting continuous monitoring and adaptive interventions through real-time control loops [17], [18], [19]. By combining emotional, physiological, and behavioral indicators, the research shifts from conceptual simulations to empirical analytics, enabling workplace environments that dynamically adjust to enhance self-confidence [20].

While earlier agent-based models conceptualized self-confidence using abstract psychological variables, many did not define explicit pathways for sensor-level modulation or adaptive feedback compatible with real IoT systems. Although sensor inputs are simulated in this study, their structure, prioritization, and functional roles are grounded in established findings on wearable sensing, stress, affect monitoring, and physiological computing toolchains. This work therefore advances prior models by establishing a sensor-ready cognitive dynamics framework, representing a necessary intermediate step between purely theoretical modeling and real-world deployment [21], [22], [23], [24]

This research contributes an IoT-integrated framework for modeling workplace self-confidence by combining physiological, behavioral, and environmental sensing into a unified analytical structure. The research contribution is the introduction of a sensor-to-cognitive mapping mechanism that enables direct adjustment of hidden psychological states at the sensor level. The framework incorporates deep-learning-inspired, system-dynamics-based adaptive learning dynamics to regulate self-esteem, self-efficacy, and self-concept. Simulation results show improved convergence stability and steady-state outcomes compared to non-IoT cognitive models, demonstrating theoretical stability rather than real-world behavioral validation**.** This provides a sensor-ready foundation for future empirical validation.

The remainder of this paper is organized as follows: In Section II, the concept of work is presented. Section III describes methodology. Section IV provides an overview of the results with discussion. Finally, Section V concludes by recapping the primary insights of this paper.

II. CONCEPTS

A. IOT Architecture & Sensor Framework

The Internet of Things (IoT) architecture typically consists of multiple layers: the Perception Layer (sensors and actuators), the Network Layer (communication protocols), the Processing Layer (data analysis and storage), and the Application Layer (user interfaces and service [5], [25], [26]. In workplace environments, IoT sensors monitor various aspects such as employee activity, environmental conditions, and equipment status [27]. These sensors collect data that is transmitted through the network layer to processing units, where it is analyzed to derive actionable insights. The integration of IoT sensors with algorithms enables real-time monitoring and decision-making, enhancing workplace efficiency and safety [25].

B. Proposed IOT Sensors, Their Roles and Priority in Workplace

The proposed conceptual sensor framework integrates diverse IoT sensors to monitor workplace self-confidence and performance through five key nodes: Motivation, Effort, Social Persuasion, Knowledge, and Performance. Motivation is assessed via HRV, EDA, and Pupillometry, reflecting engagement, emotional arousal, and cognitive effort [27], [28], [29]. Effort is captured using EEG and Pupillometry to evaluate cognitive workload [30], [31], [32], [33]. Social Persuasion employs Noise, Lighting, and Smart Desk Sensors to track environmental and interpersonal influences [34], [35], [36]. Knowledge acquisition uses EEG and Accelerometers to monitor flow states and engagement [37], [38]. Performance integrates all node inputs, and environmental data to represent key physiological, cognitive, and situational factors, ensuring meaningful sensor input for cognitive modeling and deep learning [39], [40], [41].

Sensor prioritization ensures that each node contributes the most meaningful and reliable data to the model. In Motivation, HRV is prioritized for its strong link to emotional arousal and engagement, followed by EDA for stress detection and Pupillometry for cognitive effort [11], [41], [42]. For Effort, EEG ranks highest due to its direct measurement of mental workload, with Pupillometry offering fast, non-invasive validation [43], [44]. Within Social Persuasion, Lighting Sensors take priority for their proven impact on mood and behavior, while Noise and Smart Desk Sensors provide contextual insights into social and environmental dynamics [45], [46], [47], [48]. Knowledge prioritizes EEG for capturing attention and learning flow, with Accelerometers detecting movement and engagement levels during active tasks [49], [50]. For Performance, a multi-sensor combination of HRV, EDA, and environmental detectors such as smoke , fire, gas captures both physiological resilience and external safety factors. This structured hierarchy ensures the most influential, reliable, and contextually relevant signals guide cognitive modeling and predictive analytics [51], [52], [53].

C. IoT Sensors Mapped to Psychological Constructs

The The proposed framework maps sensor data to specific psychological nodes to justify their inclusion. Motivation is influenced by intrinsic ability (Ab), LEf, and LEs, with HRV, EDA, and Pupillometry providing complementary physiological indicators [54], [55], [56], [57]. Effort is shaped by motivation and job demands, captured via EEG and Pupillometry [58], [59]. Social Persuasion is influenced by environmental cues measured with Lighting, Noise, and Smart Desk Sensors [36]. Knowledge acquisition relies on cognitive ability and engagement, monitored through EEG and accelerometers [46], [60]. Performance integrates these factors, with intrinsic ability having the greatest influence, followed by self-esteem, self-efficacy, and effort. Physiological sensors (HRV, EDA) track stress and recovery [55], [61] and environmental sensors (Flame, Smoke, Gas) detect workplace hazards that can impair cognitive and physical performance [62], [63]. This mapping conceptually links IoT measurements to the psychological constructs underlying workplace self-confidence and performance.

D. IoT Architecture Supporting the Sensor Framework and Deep Learning

The IoT architecture provides the backbone for the sensor framework by enabling seamless collection, transmission, and integration of multi-modal data. Sensors in the Perception Layer capture physiological, behavioral, and environmental signals, which are transmitted via the Network Layer to the Processing Layer for preliminary analysis and feature extraction [1], [64], [65], [66]. This processed data feeds into deep learning models, where nodes provide targeted features reflecting cognitive and behavioral states [67], [68]. The Application Layer then delivers actionable insights, supporting real-time monitoring, robust prediction of workplace self-confidence and performance, and scalable cognitive agent modeling [69].

III. METHODOLOGY

Although the proposed architecture adopts a layered, neural-inspired representation, it is not a conventional supervised deep neural network trained via gradient descent on labeled datasets. Instead, the framework follows a deep-learning-inspired temporal-causal system-dynamics approach, where latent cognitive states and adaptive coupling weights evolve through bounded nonlinear update equations driven by IoT sensor feedback. The term "hidden layer" in Fig. 1. denotes latent cognitive representations rather than classical trainable hidden layers in backpropagation-based pipeline.

The term deep learning in this study refers to the multi-layer representation of cognitive processes and adaptive parameter evolution, rather than loss-minimizing gradient-descent training. Learning is realized through temporal error-correction and feedback-modulated adaptation, conceptually aligned with biologically plausible learning mechanisms such as feedback alignment and random feedback pathways, which have been shown to support effective learning without explicit backpropagation [70],[71]. Consequently, model evaluation focuses on dynamic behavior, convergence, and stability properties of the adaptive system under continuous IoT feedback, rather than training/ validation/ testing splits used in supervised learning [72], [73].

The methodology of this study aims to enhance the original cognitive learning model by integrating IoT-driven feedback and dynamic weighting mechanisms to improve the accuracy of self-confidence and performance analytics., focusing on mathematical refinement of node equations and adaptive learning dynamics to better represent real-time human factors under sensor-based monitoring of these 5 nodes, Motivation, Effort, Knowledge, Social Persuasion and Performance. Then, modify the hidden layer behavior in the deep learning model to allow adaptive weight updates based on sensor-driven errors.

The proposed model has IoT sensors in the hidden layers, categorized into three distinct types, as shown in Fig. 1. Table 1 below explains the labels used in Fig. 1. As the original framework equations captured temporal changes in learning parameters but lacked external sensory feedback and adaptive weighting based on it, to address this gap, the improved model introduced IoT-sensor–dependent modulation terms for these 5 nodes, where physiological and behavioral sensor data dynamically influence node activation and learning weights. Table 2 and 3 contains a list of nomenclatures for formal representation of the node, IoT-derived variables and respective sorts of characteristics, along with their model states and responsibilities.

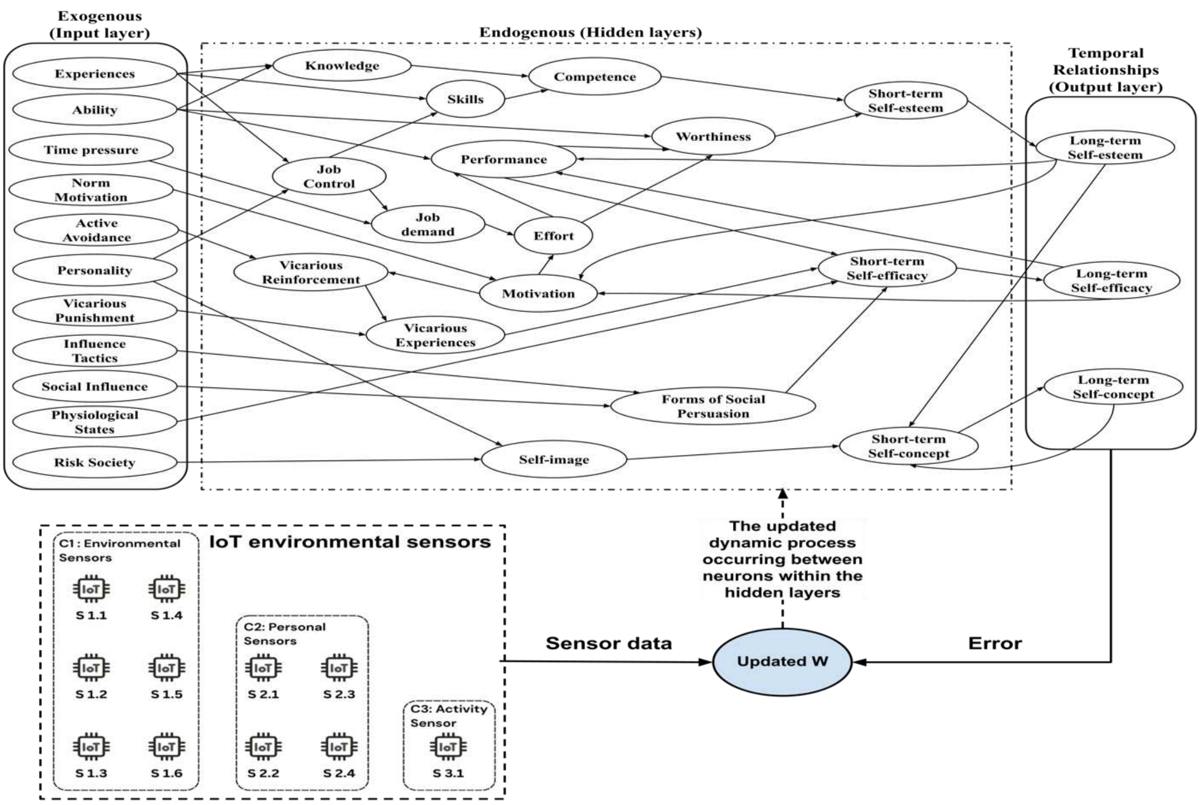

Fig. 1. Layered neural-inspired cognitive agent model with IoT driven temporal adaptation

TABLE I. IOT CONCEPTUAL LABEL

Concept	Label
Category 1 Environmental Sensors	C1
Category 2 Personal Sensors	C2
Category 3 Activity Sensor	C3
Flame Sensor	S 1.1
Smoke Detector	S 1.2
Gas Sensor	S 1.3

Noise Sensor	S 1.4
Smart Desk Sensor	S 1.5
Lighting Sensor	S 1.6
Heart Rate Variability (HRV) Sensor	S 2.1
Electrodermal Activity (EDA) Sensor	S 2.2
Electroencephalography (EEG) Neuro Scan	S 2.3
Pupillometry (Pup) Eye-tracking Sensor	S 2.4
Accelerometer (ACC)	S 3.1

TABLE II. FORMALIZED CONCEPT

Concept	Formalization
Effort	Ef
Motivation	Mo
Forms of Social Persuasion	Sp
Performance	Pe
Knowledge	Kn
Motivation Heart Rate Variability Sensor	MoHRV
Motivation Electrodermal Sensor	MoEDA
Motivation Pupillometry Sensor	MoPup
Effort Electroencephalography Sensor	EfEEG
Effort Pupillometry Sensor	EfPup
Knowledge Electroencephalography Sensor	KnEEG
Knowledge Accelerometer Sensor	KnACC
Performance Heart Rate Variability Sensor	PeHRV
Performance Electrodermal Sensor	PeEDA
Performance Flame Sensor	PeFir
Performance Smoke Sensor	PeSmo
Performance Gas Sensor	PeGas
Noise sensor	SpNOS
Smart Desk Sensor	SpSDS
Lighting Sensor	SpLTS

TABLE III. MODEL STATES FOR NETWORK CHARACTERISTICS

Aggregation	Evaluating a state's many effects	αMonew, βMonew, δMonew, αEfnew, δPenew, βPenew, γPenew, λPenew, αPenew, βSpnew, αSpnew, γSpnew, αKnnew
Timing	Speed Factors	ηLMonew, ηLEfnew ηLPenew, ηLKnnew, ηLSpnew

For example, the sensor for Mo, heart rate variability (HRV), electrodermal activity (EDA), pupil dilation (Pup) as additional inputs and the data of these sensors incorporate with Mo within a weighted feedback term and the equation for Mo is as follow,

$$\mathrm{Mo_{new}}(t) = \mathrm{Mo}(t) \,.\Bigg[1 - \Bigg(\Big(\alpha_{\mathrm{Monew}} \cdot \mathrm{MoHRV}(t) + (1-\alpha_{\mathrm{Monew}}) \cdot (\beta_{\mathrm{Monew}} \cdot \mathrm{MoEDA}(t) + (1-\beta_{\mathrm{Monew}}) \cdot \mathrm{MoPup}(t))\Big) \cdot \delta_{\mathrm{Monew}} + (1-\delta_{\mathrm{Monew}}) \cdot \frac{(\mathrm{L_{Ef}}(t) + \mathrm{L_{Es}}(t))}{2}\Bigg)\Bigg] \tag{1}$$

Equation (2) updates the Effort node by multiplicatively attenuating the current effort state $\mathrm{Ef}(t)$ according to real-time cognitive workload signals. The attenuation term is a weighted mixture of EEG (primary) and pupillometry (secondary) evidence: α_{ef}weights EEG vs. 1-α_{ef} for pupil dilation. In short, larger EEG/pupil indicators of workload reduce the node's effective value for the next step, so the node reflects instantaneous cognitive load measured by physiological sensors. This is a sensor-driven modulation that makes the Effort node responsive to neurophysiological signals.

$$\mathrm{Ef_{new}}(t) = \mathrm{Ef}(t).\big(1 - (\alpha_{\mathrm{ef}} \cdot \mathrm{EfEEG}(t) + (1-\alpha_{\mathrm{ef}}) \cdot \mathrm{EfPup}(t))\big) \tag{2}$$

Equation (3) computes the Social Persuasion node as the current social state $S_p(t)$ scaled down by an environment-driven factor. The bracketed term is a convex combination prioritizing lighting sensor influence (α_{sp} on LTS) vs. a mix of noise and smart-desk signals: υ_{sp} weights Noise (SpNOS) against Smart-desk (SpSDS). Thus lighting, noise, and desk sensors jointly reduce (or preserve) the social-persuasion score depending on measured environmental conditions. This ties social influence on immediate environmental context (light/noise/desk), letting the node reflect situational social cues.

$$SP_{new}(t) = S_p(t) \cdot \Big(1 - \big(\alpha_{sp} \cdot LTS(t) + (1-\alpha_{sp}) \cdot (\upsilon_{sp} \cdot \mathrm{SpNOS}(t) + (1-\upsilon_{sp}) \cdot SpSDS(t))\big)\Big) \tag{3}$$

Equation (4) updates the Knowledge node multiplicatively by downscaling the current knowledge $K_n(t)$ according to cognitive/behavioral sensors: a weighted mix of EEG (KnEEG) and accelerometer activity (KnACC). The weight α_{kn} sets the relative trust in EEG vs. accelerometry. Effectively, higher measured signals (e.g., reduced attention on EEG or lower engaged movement) reduce the Knowledge node, so the node indexes immediate learning/engagement as seen through neurophysiological and motion sensors.

$$Kn_{new}(t) = K_n(t) \cdot \big(1 - (\alpha_{kn} \cdot \mathrm{KnEEG}(t) + (1 - \alpha_{kn}) \cdot \mathrm{KnACC}(t))\big) \quad (4)$$

Equation (5) is a two-stage expression for Performance: Baseline blend: The first multiplicative factor blends prior performance $P_e(t)$ (with weight δ_{pe}) and current physiological inputs (with weight 1-δ_{pe}). Those physiological inputs themselves are a convex mix of HRV (PeHRV) and EDA (PeEDA) controlled by λ_{pe}. This produces a baseline performance prediction that combines memory (past performance) and current physiological state. Environmental / risk suppression: The second factor (1 - environmental hazard term)) reduces the baseline score according to hazard and contextual sensors. That inner hazard term mixes direct safety cues (FIR), and a nested combination of Smoke (PeSmo), Gas (PeGas) weighted by β_{pe}, then gated by γ_{pe} against a contextual average of latent environment-supports $(L_{Es}(t) + L_{Ef}(t))/2$. The weighting α_{pe} sets the relative influence of immediate FIRE vs. the other environment measures.

$$Pe_{new}(t) = \Big(\delta_{pe} \cdot P_e(t) + (1 - \delta_{pe}) \cdot \big(\lambda_{pe} \cdot \mathrm{PeHRV}(t) + (1 - \lambda_{pe}) \cdot \mathrm{PeEDA}(t)\big)\Big) \cdot \left(1 - \left(\alpha_{pe} \cdot \mathrm{PeFir}(t) + (1 - \alpha_{pe}) \cdot \left(\big(\beta_{pe} \cdot \mathrm{PeSmo}(t) + (1 - \beta_{pe}) \cdot \mathrm{PeGas}(t)\big) \cdot \gamma_{pe} + (1 - \gamma_{pe}) \cdot \frac{L_{Es}(t) + L_{Ef}(t)}{2}\right)\right)\right) \quad (5)$$

The multiplicative structure in Eqs. (1)–(5) models IoT sensor influence as propotional modulation of cognitive states, preserving normalized bounds [0,1] and supporting stable convergence. This modification follows an iterative update rule where the new state of each node, which is computed based on the difference between the current observed value and its predicted value in which equation is calculated using t+Δt, scaled by a learning rate based on real-time error propagation and sensor variability with η as the rate of change for all temporal characteristics throughout time as mentioned in Table 2.

$$LMo_{new}(t + \Delta t) = LMo_{new}(t) + \eta \cdot \big(Mo_{new}(t) - LMo_{new}(t)\big) \cdot \big(1 - LMo_{new}(t)\big) \cdot LMo_{new}(t-1) \cdot \Delta t \quad (6)$$

The update rule in Eq. (6) implements a temporal error-correction adaptation (system dynamics learning) rather than loss-minimizing backpropagation/ gradient descent. The coupling weight is adjusted using the discrepancy between the latest estimate and the sensor-modulated state to promote smooth convergence under fluctuating inputs. Equations (7) to (10) represent the latent-state adaptation layer for Effort, Social Persuasion, Knowledge, and Performance, respectively. Each follows a common nonlinear update rule that incrementally adjusts the latent variable $L_x(t)$ (where $X \in \{\mathrm{Ef}, \mathrm{Sp}, \mathrm{Kn}, \mathrm{Pe}\}$) toward its observed value $X_{new}(t-1)$ based on a learning rate parameter η and a logistic modulation term (1 - $L_x(t)$) $L_x(t)$ scaled by the integration step Δt. This formulation ensures bounded, smooth convergence of latent estimates, preventing abrupt oscillations while allowing gradual adaptation to changing sensor-derived observations. In effect, these equations act as stabilized learning filters, transforming raw, often noisy physiological or behavioral measurements into internally consistent latent representations that capture sustained cognitive or behavioral tendencies over time.

$$LEf_{new}(t + \Delta t) = LEf_{new}(t) + \eta \cdot (Ef_{new}(t) - LEf_{new}(t)) \cdot (1 - LEf_{new}(t)) \cdot LEf_{new}(t) \cdot \Delta t \quad (7)$$

To approximate real IoT behavior, the proposed framework supports simulated sensor streams with optional additive noise and slow drift, followed by normalization and clipping to the [0,1] range. In the present simulation, normalized sensor signals were used to focus on validating convergence and stability of the proposed temporal learning dynamics. This provides a simplified representation of measurement variability while preserving numerical stability for convergence evaluation. The proposed equations (1) to (10) were implemented using Python-based numerical simulation across 800-time steps to model temporal evolution. Each psychological node was initialized with normalized values between 0 and 1, representing internal states. IoT signals were simulated as continuous sensor feedback inputs. The learning parameters (αMonew, β Monew, δMonew) were tuned empirically to ensure stability. Comparative analysis between the baseline (no IoT) and enhanced (IoT-driven) systems was visualized using time-series plots, demonstrating smoother transitions and improved convergence behavior.

With the internal state representation of each cognitive factor becomes sensitive to environmental and physiological cues, incorporating IoT-based feedback significantly strengthens the system's data analytics capability, making it more responsive and adaptive to complex real-world variations

$$LSp_{new}(t + \Delta t) = LSp_{new}(t) + \eta \cdot (SP_{new}(t) - LSp_{new}(t)) \cdot (1 - LSp_{new}(t)) \cdot LSp_{new}(t) \cdot \Delta t \quad (8)$$

$$LKn_{new}(t+\Delta t) = LKn_{new}(t) + \eta \cdot (Kn_{new}(t) - LKn_{new}(t)) \cdot (1 - LKn_{new}(t)) \cdot LKn_{new}(t) \cdot \Delta t \quad (9)$$

$$LPe_{new}(t+\Delta t) = LPe_{new}(t) + \eta \cdot (Pe_{new}(t) - LPe_{new}(t)) \cdot (1 - LPe_{new}(t)) \cdot LPe_{new}(t) \cdot \Delta t \quad (10)$$

Parameter values were selected to ensure bounded latent states, stable convergence, and consistency with cognitive agent modeling assumptions. Tuning was performed through iterative simulation and sensitivity analysis, consistent with established validation practices for agent-based and simulation models [74], [75]. To approximate real IoT measurement variability, sensor streams were modeled as normalized signals with additive noise and slow drift, reflecting common wearable sensing artifacts and signal instability [76], [77], [78], [79].

Implementation includes IoT signal acquisition, preprocessing, mapping to latent cognitive states, and bounded temporal updates of adaptive couplings, following pipelines commonly used in wearable stress and mental-state monitoring studies [76], [77], [80]. Fig 2 shows the overall flowchart of the framework.

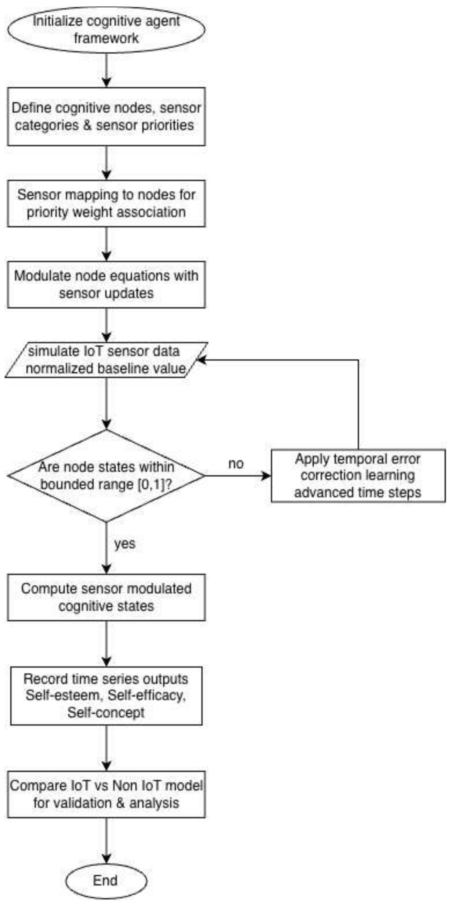

Fig. 2. Overall Methodology Flowchart

As the framework is system-dynamics / agent-based rather than a supervised deep learning model, validation is conducted via simulation-based convergence and stability analysis, consistent with recommended practices for such models [74], [75] The architecture is deep-learning–inspired due to its layered latent representation and biologically plausible learning perspective supported by feedback-alignment research [71]

Limitations include sensitivity to parameter initialization, sensor noise and artifacts, and the lack of real-world deployment data, motivating future empirical validation [76], [77], [78], [79].

IV. Results and Discussion

A. Analyzing the results

This section presents the behavioral development of fictitious workers under the IoT-enhanced stimulation model and compares it with the previous non-IoT model. Four simulation cases were shown to study how physiological and environmental IoT sensors influence cognitive stability, motivation, and self-confidence elements. The same cognitive equations from the previous model were maintained, while IoT stimulation factors were integrated to enhance learning dynamics.

As physical IoT sensors were not deployed, physiological inputs were simulated using stochastic noise, low-frequency drift, and transient perturbations to approximate real-world bio-signal behavior. Adaptive learning rates and sensor-weighting mechanisms were applied to ensure convergence stability. Although empirical validation using datasets such as DEAP and WESAD is beyond the scope of this simulation-based study, the proposed framework is designed to be compatible with real EEG, EDA, and HRV data.

The results show that the IoT-enhanced model achieves smoother learning trajectories, faster convergence, and higher steady-state levels of self-esteem, self-efficacy, and self-concept than the non-IoT model across all scenarios. While formal statistical testing was not performed, the improvements were consistent and stable, indicating robust confidence development.

Default parameters such as Δt = 0.3, t_mix = 800, regulatory rates = 0.7, speed factors = 0.3, and weights for self-elements = 0.50 and performance = 0.25 were kept constants for all cases to ensure a direct comparison. Table 4 summarizes the initial configurations for each simulation case.

TABLE IV. Default configurations for each simulation case.

Factors	**Case #1**	**Case #2**	**Case #3**	**Case #4**
Experiences (Ex)	0.9	0.1	0.9	0.9
Personality (Pr)	0.9	0.1	0.9	0.9
Ability (Ab)	0.9	0.9	0.9	0.9
Norm Motivation (Nm)	0.9	0.9	0.9	0.9

Active Avoidance (Aa)	0.9	0.1	0.9	0.1
Vicarious Punishment (Vp)	0.9	0.1	0.9	0.1
Influence Tactics (It)	0.1	0.9	0.1	0.9
Social Influence (Si)	0.1	0.9	0.1	0.9
Time Pressure (Tp)	0.9	0.9	0.1	0.1
Physiological States (Pi)	0.9	0.1	0.9	0.1
Risk Society (Rs)	0.1	0.9	0.9	0.1

Table 4 presents the initial conditions for the four simulation cases, each reflecting a different workplace situation based on cognitive, motivational, social, and physiological factors. While the initial values vary across cases, all global parameters were kept the same to ensure a fair comparison and to isolate how these starting conditions affect confidence development and learning behavior.

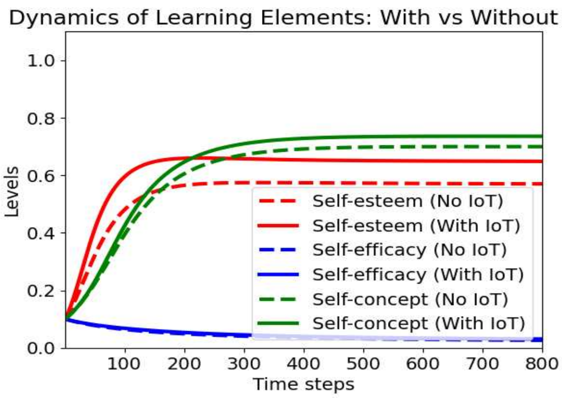

Fig. 3. Simulation result for Case 1

Case #1: In Case 1, the IoT-enhanced model shows faster improvement and higher final levels in self-esteem, self-efficacy, and self-concept compared to the non-IoT model, indicating that continuous physiological feedback strengthens cognitive stability and positive self-perception. **Figure 3 shows** that the IoT-enhanced model reaches stability more quickly and with fewer fluctuations than the non-IoT model, suggesting more robust behavior under high-readiness and high-pressure conditions.

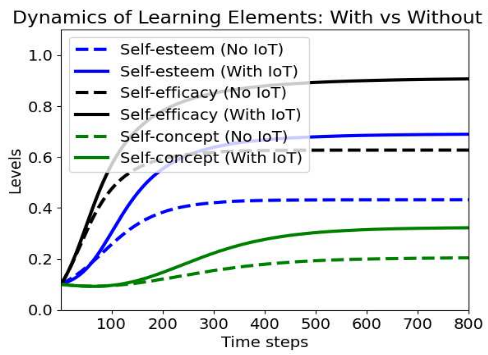

Fig. 4. Simulation result for Case 2

Case #2: In this case, when performance is driven by social influence, the non-IoT model shows declining self-efficacy, whereas the IoT-enhanced model preserves and improves it through real-time EEG, ACC, and EDA feedback. Self-esteem and self-concept also converge at higher levels, indicating that IoT inputs stabilize psychological states under social pressure. **Figure 4 shows** that under strong social pressure and low initial confidence, the IoT-enhanced model preserves smoother and higher self-belief trajectories, indicating stronger resistance to confidence decline.

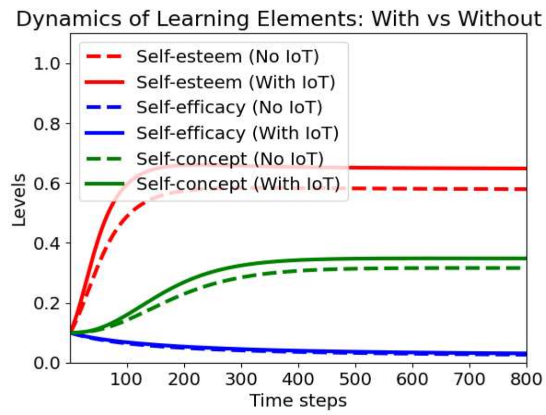

Fig. 5. Simulation result for Case 3

Case #3: This case applies low time pressure to assess cognitive responses under reduced stress. The IoT-enhanced model achieves faster convergence of self-esteem and self-concept to near-optimal levels, while self-efficacy remains stable, indicating that reduced stress combined with sensor-driven feedback supports psychological resilience and sustained motivation. **Figure 5 shows** that in low-pressure conditions, the IoT-enhanced model converges more smoothly, reflecting improved consistency even when baseline performance is already stable.

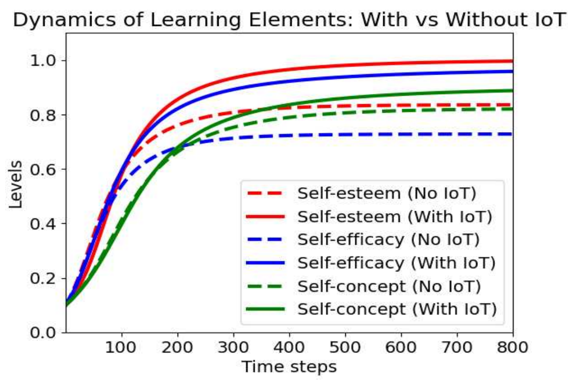

Fig. 6. Simulation result for Case 4

Case #4: In this case, physiological and environmental stressors are minimized. The IoT-enhanced model demonstrates maximum convergence across self-esteem, self-efficacy, and self-concept, indicating that the absence of negative stimuli combined with supportive IoT inputs enables optimal confidence development and long-term cognitive stability. **Figure 6 shows** that in a supportive workplace environment, the IoT-enhanced model attains the highest and most stable confidence levels, approaching near-optimal convergence.

B. Discussion

The simulation results demonstrate that the IoT-enhanced model consistently improves self-esteem, self-efficacy, and self-concept through real-time regulation of physiological and environmental inputs. This confirms that cognitive stability and confidence can be externally strengthened using sensor-based feedback, aligning with established motivational theories. These findings highlight the practical value of IoT systems for enhancing employee performance and psychological resilience, with future research focused on biometric validation and application in adaptive and group-based cognitive environments.

This real-time physiological feedback plays an active role in regulating cognitive states, helping to stabilize confidence and reduce decline under demanding workplace conditions, beyond what earlier non-IoT self-confidence models could achieve. A key strength of this work lies in its dynamic, system-level view of confidence development, focusing on how confidence evolves over time rather than on static end states. However, as the findings are derived from simulated scenarios, they do not yet capture individual differences or real-world behavioral complexity, underscoring the need for future empirical validation.

C. Evaluation

The IoT-enhanced model was assessed using established psychological properties and its adaptability through sensor integration. Simulation results confirmed theoretical validity, as self-esteem, self-efficacy, and self-concept aligned with properties P1–P4, demonstrating correct cognitive interactions and reinforcement effects. Physiological (HRV, EDA, EEG, Pup) and environmental (fire, smoke, gas) sensors enabled real-time regulation of stress and performance risk, resulting in faster convergence and higher steady-state outcomes than the non-IoT model. These findings verify that the model not only adheres to cognitive theory but also offers practical adaptability and resilience for real-world deployment.

D. Performance Comparison

In case 1, the IoT-enhanced model increases self-esteem from 0.62 to 0.7, self-efficacy from 0.82 to 0.9, and self-concept from 0.2 to 0.32, respectively, indicating improved confidence with continuous physiological regulation. In Case 2, self-efficacy increased from 0.03 to stable at 0.12, self-esteem from 0.58 to 0.68, and self-concept from 0.7 to 0.74, respectively. This shows IoT stimulation effectively prevents erosion of mental stability. In case 3, IoT inputs increased self-esteem from 0.9 to 1 and self-concept from 0.7 to 0.8, with self-efficacy remaining stable in both models. In this case IoT enhances cognitive stability rather than transforming primary learning progressions. In case 4, by removing stress-inducing factors and applying IoT support, the model increased self-esteem from 0.95 to 1.00, self-efficacy from 0.75 to 0.85, and self-concept from 0.65 to 0.75, showing that IoT systems help psychological factors fully stabilize.

V. CONCLUSION

This study presented an IoT-enhanced deep learning framework designed to model and strengthen self-confidence in workplace environments. By integrating physiological, behavioral, and environmental sensor data, the proposed system transformed traditional cognitive simulations into adaptive, data-driven analytics. The research contribution is the formulation of a sensor-ready, deep learning inspired, system-dynamics-based cognitive model that enables adaptive temporal regulation of self-confidence states. The results indicate that real-time sensor feedback and dynamic weight adjustment enable the model to learn continuously, regulate self-confidence states, and respond effectively to contextual changes, with simulation results demonstrating theoretical stability rather than real-world behavioral validation. This approach not only enhances individual performance prediction but also supports proactive well-being management within intelligent workplaces. However, sensor inputs were simulated to approximate real IoT behavior, and real-world deployment was not conducted. The framework demonstrates how combining IoT sensing with deep-learning-inspired modeling can bridge theoretical constructs and empirical analytics, offering new insights into human-centric productivity systems. Future work will focus on empirical validation using real IoT and physiological datasets.

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