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Indirect feedback alignment in deep learning for cognitive agent modeling: enhancing self-confidence analytics in the workplace

Hareebin Yuttachai[1], Billel Arbaoui[2], Yusraw O-manee[3]
[1]Faculty of Humanities and Social Sciences, Prince of Songkla University, Pattani, Thailand
[2]Department of Information and Communication Technology, Rangsit University, Pathumthani, Thailand
[3]Faculty of Humanities and Social Sciences, Phuket Rajabhat University, Phuket, Thailand

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ABSTRACT

The innovative application of indirect feedback alignment (IFA) in deep learning enhances workplace self-confidence analytics through cognitive agent modeling. IFA addresses the challenge of credit assignment in multi-layer neural networks, offering a more efficient and biologically plausible alternative to traditional backpropagation methods. The paper delves into the integration of IFA in workplace dynamics, focusing on the development of a state-determined system to describe and analyze the dynamics of self-confidence, self-concept, self-esteem, and self-efficacy among employees. Utilizing a combination of endogenous and exogenous factors, the study presents a comprehensive model that captures the complex interplay of these factors in professional settings. The research further conducts experiments to observe and analyze the behavior and pattern formation among real workers in various settings, demonstrating the practical implications of the theoretical model. The findings highlight the potential of IFA in enhancing and accelerating the components of deep learning associated with self-confidence in the workplace, contributing significantly to the fields of neural computation and cognitive psychology. The proposed method was tested in various situations to assess its alignment with the core concepts of workplace self-confidence. Mathematical analysis was employed to explore feasible equilibrium conditions and compatible cases found in the literature.

Corresponding Author:

Billel Arbaoui
Department of Information and Communication Technology, International College, Rangsit University
Pathumthani-12000, Thailand
Email: bill.a@rsu.ac.th

1. INTRODUCTION

Existing agent-based modeling approach, the study focused on the dynamic influences of environmental and personal factors on self-esteem, self-efficacy, self-concept, and self-confidence in the workplace. The computational model was validated through automated logical verification and equilibrium analysis. The model demonstrated realistic behavior patterns consistent with these factors, offering insights into the complex dynamics of workplace self-confidence and it is relationship to various personality characteristics and environmental conditions [1] which uses the concept of a state-determined system to describe dynamical systems. The other existing concept of a state-determined system to describe dynamical systems, cognitive agent model of burnout for healthcare professionals during the coronavirus disease 2019 (COVID-19) pandemic, employing a temporal-causal network model to identify and formalize burnout determinants and their causal relationships. They validated the model through mathematical analysis and automated logical verification and conducted simulation experiments to gain insights into these causal relationships, which demonstrated behaviors consistent with existing literature. The findings showed that the model could accurately depict the dynamics of burnout, highlighting critical factors such as stress, emotional exhaustion, resilience, and coping strategies. The model has potential applications in creating COVID-19 aware analytics software agents to monitor and support healthcare professionals' mental health [2]. Another existing concept of a state-determined system to describe dynamical systems, computational model to understand the temporal dynamics of anxiety in interviewees by utilizing a cognitive agent paradigm and incorporating concepts from generalized anxiety disorder theories. They formalized the model through mathematical analysis and conducted simulation experiments to examine the relationships between perceived threat, coping resources, self-efficacy, and worry. Their findings revealed that highly anxious interviewees exhibited increased levels of worry and threat perception, leading to poorer interview performance. In contrast, non-anxious interviewees, with higher self-efficacy and coping resources, managed anxiety better and performed more effectively. These results highlight the importance of self-efficacy and coping mechanisms in mitigating interview anxiety [3].

The existing concept of a state-determined system to describe dynamical systems and analytics through cognitive agent modeling approach highlights areas requiring improvement. Specifically, enhancing self-confidence analytics through cognitive agent modeling can be further developed. The concept of a state-determined system to describe dynamical systems shows potential but needs refinement to better capture the complex interplay of factors influencing an employee's self-confidence, self-concept, self-esteem, and self-efficacy.

In the context of workplace dynamics, the application of indirect feedback alignment (IFA) takes a novel turn. The focus shifts to the enhancement of self-confidence analytics through cognitive agent modeling. Cognitive agent modeling in this realm employs the concept of a state-determined system to describe the dynamical systems where the current state dictates future behavior. Self-confidence analytics through cognitive agent modeling approach [1] is instrumental in depicting the complex interplay of various factors influencing an employee's self-confidence, self-concept, self-esteem, and self-efficacy within the workplace. The landscape of deep learning and cognitive agent modeling has been significantly advanced through the introduction of IFA. Originally developed by Nøkland in 2016 [4]–[6], IFA addresses the critical challenge of credit assignment in multi-layer neural networks, a crucial aspect in the field of neural computation and learning processes. This innovative algorithm marks a departure from traditional backpropagation methods by introducing a simplified feedback pathway and reusing the unmodified feedforward pathway for generating teaching signals. These modifications not only enhance the efficiency of learning processes but also align more closely with the biological plausibility of neural computation seen in natural systems like the human brain.

The integration of IFA in self-confidence analytics through cognitive agent modeling approach enhances the understanding of complex workplace dynamics. By mimicking the balance between internal cognitive mechanisms and external influences, IFA-based models offer a more nuanced and holistic view of employee psychology. This approach not only addresses the practical challenges in neural network training but also resonates with the principles of managing complex systems, thereby providing a more efficient and biologically plausible method in the realm of deep learning. The proposed method for implementing IFA in enhancing deep learning of workplace self-confidence reflects a pioneering step in the intersection of neural computation, cognitive psychology, and organizational behavior. It aims to provide a comprehensive understanding of the dynamics at play in shaping an employee's psychological makeup in the workplace, focusing on self-confidence as a key driver of professional performance and well-being.

The paper progresses through several key sections, starting with indirect feedback alignment, which delves into the IFA algorithm's role in neural networks, and it is an innovative approach to the credit assignment challenge. This is followed by self-confidence at workplace: cognitive agent modeling and analysis, exploring the dynamics of self-confidence in professional settings through cognitive agent modeling. The method section discusses the application of IFA in enhancing deep learning for workplace self-confidence, highlighting various theories that influence this process. The comparison of experiments and equilibrium analysis section describes the practical application of these methodologies in real-world settings to analyze worker behaviors and patterns as well as mathematical analysis. Finally, the conclusion section summarizes the study's findings, demonstrating how IFA can enhance and accelerate components of deep learning associated with self-confidence in the workplace.

2. INDIRECT FEEDBACK ALIGNMENT

The IFA algorithm, developed by Nøkland in 2016 [4] addresses the critical challenge of credit assignment in multi-layer neural networks. Figure 1(a) illustrates the "credit assignment" problem [7]–[9], highlighting the behavioral effects of changes to synaptic connections in the brain's neural network. It shows how modifications in the primary sensory area (depicted in black) and higher sensory areas (depicted in blue) can influence the associative concept area and motor output area (depicted in red). This diagram underscores the dependency of behavioral effects on the status of these synaptic connections, drawing a parallel to how IFA manages credit assignment in artificial neural networks (ANN) by simplifying and optimizing feedback pathways.

This challenge, illustrated in the context of the neocortex, involves determining how synapses in earlier processing stages receive 'credit' for their impact on behavior or cognition. This credit depends on downstream synaptic connections that link early pathways to later computations. While traditional backpropagation of error algorithms solves this by calculating the credit for each synapse in the hidden layer using downstream synaptic weights, this method is not considered biologically plausible. IFA presents a novel approach with two key features: i) it introduces a simplified feedback pathway using only a single matrix of synapses, thereby avoiding the complexity of traditional backpropagation; ii) it reuses the unmodified feedforward pathway to produce teaching signals, effectively bypassing the need for weight transport mechanisms used in backpropagation. These characteristics make IFA not only efficient but also a potentially more biologically plausible model for addressing the credit assignment problem in neural network learning processes [3], [5]. The equation for IFA can be understood in the context of how it differs from the traditional backpropagation algorithm. In backpropagation, the update rule for each weight W in the network is typically represented as (1).

$$W_{new} = W_{old} - \eta \cdot \frac{\partial L}{\partial W} \tag{1}$$

where:
W_{old} : the current weight
η : the learning rate
L : the loss function
$\frac{\partial L}{\partial W}$: the gradient of the loss with respect to the weight W

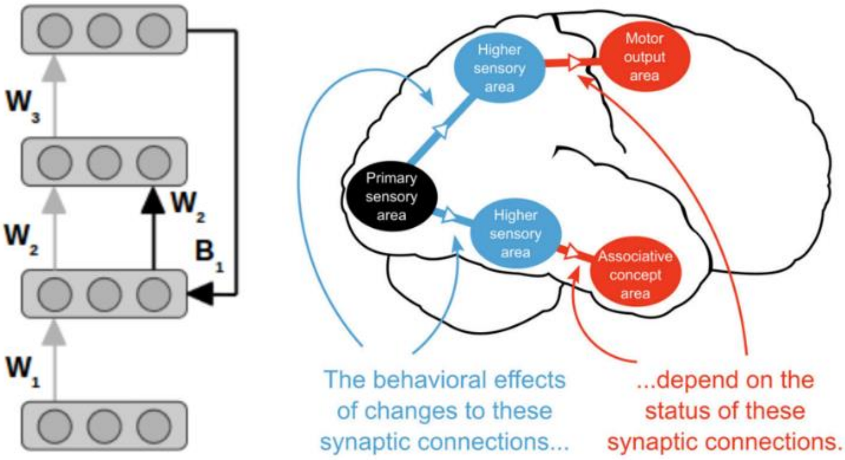
In backpropagation, this gradient is computed by propagating the error backward through the same path as the forward pass, typically using the transpose of the forward weight matrices. In contrast, IFA modifies the way the gradient $\frac{\partial L}{\partial W}$ is computed during the backward pass. The equation for weight update in IFA can be represented as (2).

$$W_{new} = W_{old} - \eta \cdot \delta \cdot B \tag{2}$$

Here, δ is the error signal derived from the loss function (similar to backpropagation), and B is a random, fixed feedback matrix, which is not necessarily the transpose of any forward weight matrix.

The key difference is the use of B instead of the transposed weight matrix from the forward pass. This B matrix remains fixed during training and is not updated like the weights in the forward path. It provides an indirect way of aligning the feedback for learning. The diagram in Figure 1(b) showcases a neural network using IFA for training. It shows three layers of a neural network connected by weight matrices W_1, W_2, and W_3 with data flowing upward during the forward pass. IFA diverges from traditional training methods during the backward pass, where it employs a random fixed feedback matrix B_1 to propagate the error signal back through the network. This matrix is separate from the forward pass weight matrices and remains constant, offering a computationally efficient and biologically plausible alternative to the traditional backpropagation algorithm. The indirect alignment aims to provide a viable training signal to adjust the weights, fostering learning without the exact gradients.

Implementing IFA requires the complex structure of deep learning networks. As illustrated in Figure 1, the forward pass through these networks is essential for IFA's strategy, where a fixed feedback matrix enables error signal propagation without direct gradient calculations. Thus, the depth of deep learning models (such as self-confidence at workplace: cognitive agent modeling and analysis [1]) is essential to IFA's cutting-edge training methodology. For example, human resource (HR) managers can apply IFA in employee training to boost the analytics of self-confidence and job performance. Deep learning technologies combined with data analytics significantly improve employee performance [7], [10]. Sadowski [11] highlighted that advanced technology such as deep learning can help HR managers develop policies to boost self-confidence and improve decision-making. Combining IFA with data analytics technologies can lead to sustainable learning and growth for employees [12], [13].



(a) (b)

Figure 1. IFA method representation (a) neural network using IFA for training [4], (b) the "credit assignment" problem in the brain [7]

3. SELF-CONFIDENCE AT WORKPLACE: COGNITIVE AGENT MODELING AND ANALYSIS

In this section, it is explained the results of research and at the same time is given a comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [11], [13]. Self-confidence at workplace: cognitive agent modeling and analysis [1] discusses the idea of a state-determined system, which is used to describe a dynamical system where the current state always dictates it is distinct future behavior [14], [15]. The concept of a state-determined system, as it pertains to the principles of temporal factorization and criterial causation, is examined in the context of self-confidence at workplace: cognitive agent modeling and analysis. This method can be utilized for depicting representations in both graphical and numerical forms. The illustration often takes the form of a complex network, comprising nodes represented by circles and arrows. In Figure 2, a dynamical process, symbolized by an arrow, connects a series of elements represented as circles, to elements, which is also depicted as a circle. The requirements for causality are intelligent in this manner. Mathematical formulations can be employed to specify dynamical systems. Based on the literature review, in Figure 2, a range of endogenous (hidden layers, internal or local) and exogenous (input layer, external or non-local) characteristics are used to identify determinants. Exogenous elements, derived from social and environmental specifications, furnish a set of inputs for the model. Conversely, endogenous components, stemming from both social and environmental specifications or mechanisms, provide the model with a series of connections to various factors and theories. Furthermore, the model outputs (output layer) the temporal relationship effects of self-concept, self-efficacy, and self-esteem in the workplace. The following are the paper's findings: The worker in Case #1, which highlights deep learning uses, indicates a strong personality and ability that are enhanced by a wealth of knowledge and motivation, resulting in a positive self-concept at work. Case #2, which makes use of methods of deep learning as well, describes an individual with good ability, social influence, motivation, and persuasion techniques who has a high level of self-efficacy at work. Case #3 is similar to Case #1 in the context of deep learning, but it varies in that there is less time pressure, which helps the person feel good about himself. Finally, Case #4 integrates deep learning and, like the other cases, stands out for not involving a risk society, vicarious punishment, or deliberate avoidance at work. It also lacks a physiological history of stress-related illnesses like depression or anxiety. The employee develops a strong sense of self and is highly confident as a result of this situation. Each scenario is backed with simulation traces in the corresponding study figures, which are based on deep learning approaches.

Forward propagation in a neural network, essential for calculating the network's output from input data, is akin to a state-determined system as discussed in self-confidence at workplace: cognitive agent modeling and analysis. In such systems, the current state dictates future behavior, paralleling how each neural network layer transforms data using weights and activation functions. However, deep networks face challenges reminiscent of complex network dynamics. Vanishing gradients, where gradients shrink as they propagate back, impede weight updates in early layers, akin to a system's elements losing influence over time. Exploding gradients present the opposite problem, akin to an element exerting disproportionate influence, leading to unstable training and divergent outcomes. Additionally, computational complexity increases with more layers, similar to the increasing complexity in a network with more nodes and connections. This complexity mirrors the intricate interplay of endogenous and exogenous factors in cognitive agent models, where inputs (exogenous elements) and internal connections (endogenous components) determine the network's behavior, ultimately affecting outputs like self-concept, self-esteem and self-efficacy in a workplace context.

Moreover, IFA's reuse of the unmodified feedforward pathway for generating teaching signals parallels the model's use of existing cognitive structures (self-concept, self-esteem, self-efficacy) to understand complex workplace dynamics. This approach not only enhances efficiency but also aligns more closely with how natural systems, like the human brain, are theorized to operate. It effectively mirrors the balance between internal mechanisms and external influences in cognitive agent modeling, thereby addressing both the practical and theoretical challenges in neural network training. Thus, IFA's design and functionality resonate with the principles of managing complex systems, offering a more efficient and potentially biologically plausible method in the realm of deep learning.

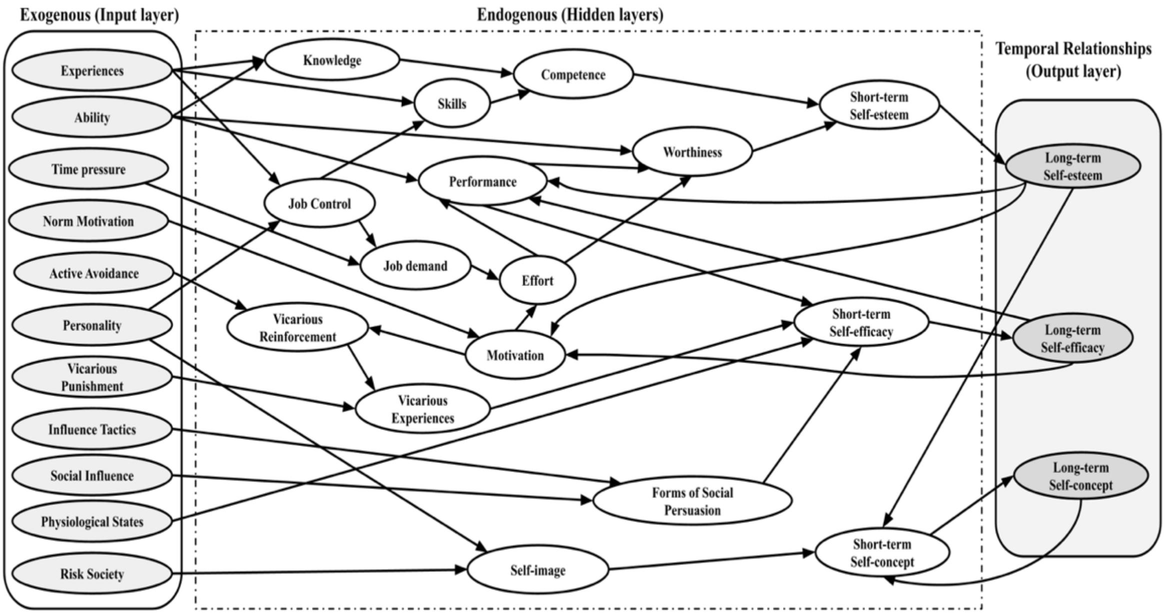


Figure 2. Self-confidence model for deep learning [1]

4. METHOD

The proposed IFA for enhancing the deep learning of workplace self-confidence needs to highlight several theories. These theories assist in providing feedback to the deep learning algorithm for adjusting the weight matrix parameters. To highlight these theories, it is necessary to first consider the long-term effects of low or high output from the layers on the input layers.

In the first scenario of IFA, which is based on the third case in self-confidence model [1], the difference lies in the reduced time pressure. This reduction helps the person feel good about themselves. "*What happens to a worker's motivation* **(***Nm***)** *and abilities* **(***Ab***)** *if they are in a long-term state of low self-efficacy and high self-esteem?*". As depicted in (3) and (5), feedback occurred during training to correct the loss function. The fixed feedback matrix is the prediction of the workers' motivation and abilities, based on learning rates η_{LNm} and η_{LAb} as shown in (4) and (6), respectively.

For motivation, self-determination theory [16] can be applied here. This theory suggests that motivation is driven by the need for competence, autonomy, and relatedness. In the context of low self-efficacy at the workplace leading to decreased intrinsic motivation. The worker might not feel capable or competent in certain tasks, which diminishes their motivation to engage in those tasks despite their high self-esteem.

$$Nm(t)_{new} = Nm(t)_{old} \cdot \left(1 - \left(\frac{\sum_{i=1}^{n} y_i(t)}{N}\right)\right) \tag{3}$$

$$LNm(t + \Delta t) = LNm(t) + \eta_{LNm} \cdot \left(Nm(t)_{new} - LNm(t)\right) . \Delta t \tag{4}$$

where, t is time steps, Nm is normalized motivation of the worker, LNm is long-term motivation of the worker, y_i is one node in the output layer, N is Total number of nodes in the output layer, and Δt is change process.

Bandura's social learning theory [17], especially the concept of self-efficacy, is directly relevant. Bandura posited that self-efficacy influences the choice of activities, effort, and persistence in the workplace context. A worker with low self-efficacy in certain skills might avoid activities at the workplace that require those skills, leading to underutilization and underdevelopment of those abilities. This aligns with the idea that belief in one's capabilities plays a crucial role in how one approaches goals, tasks, and challenges at the workplace.

$$LAb(t)_{new} = Ab(t)_{old} \cdot \left(1 - \left(\frac{\sum_{i=1}^{n} y_i(t)}{N}\right)\right) \tag{5}$$

$$LAb(t + \Delta t) = LAb(t) + \eta_{LAb} \cdot \left(Ab(t)_{new} - LAb(t)\right). \Delta t \tag{6}$$

where Ab is normalized abilities of the worker and LAb is long-term abilities of the worker.

In the first case of IFA, which is based on the third case in self-confidence model [1], the difference lies in the reduced time pressure. This reduction helps the person feel good about themselves. "*What happens to a worker's motivation* **(***Nm***)** and *abilities* **(***Ab***)** *if they are in a long-term state of low self-efficacy and high self-esteem?*". As represented in (3) and (5), the feedback happened while training to correct the loss furcation. The fixed feedback matrix is the production of these worker's motivation and abilities based on learning rates η_{LNm} and η_{LAb} as shown in (4) and (6). As depicted in (3) and (5), feedback occurred during training to correct the loss function. The fixed feedback matrix is the prediction of the workers' motivation and abilities, based on learning rates η_{LNm} and η_{LAb} as shown in (4) and (6), respectively.

In the second scenario of IFA, which is based on the second case in self-confidence model [1], an individual is described as possessing notable ability, social influence, motivation, and persuasion skills, leading to high self-efficacy in the workplace. The question arises, *"What is the impact on a worker's motivation* **(***Nm***)** *and social influence* **(***Si***)** *when they consistently experience low self-concept yet maintain high self-efficacy?*". As illustrated in (3) and (7), corrective feedback is applied during training to address the loss function. This process is encapsulated in the fixed feedback matrix, which forecasts the worker's motivation and social influence. These are determined by learning rates η_{LNm} and η_{LSi}, as demonstrated in (4) and (8), respectively.

Understanding the impact of low self-concept on norm motivation and social influence can be effectively explained through various psychological theories. Social identity theory, developed [18], posits that self-concept is influenced by group memberships. In this light, individuals with low self-concept might feel less connected to social groups, leading to reduced motivation to conform to group norms. This idea is further extended by self-categorization theory [19], which suggests that individuals classify themselves into different groups. A low self-concept could result in less identification with these groups and their associated norms. On the front of social influence (Si), the theory of reasoned action [20] implies that an individual's behavior is shaped by their intentions, which are influenced by their attitudes and perceived norms. For someone with a low self-concept, the attitudes towards these norms might be weaker, diminishing the impact of social influence. Additionally, minority influence theory [21] illustrates how individuals or smaller groups can sway larger groups. An individual with a low self-concept, particularly when combined with high self-efficacy, might be less susceptible to the influence of the majority. These theories collectively shed light on how self-concept shapes an individual's response to social norms and influences.

$$Si(t)_{new} = Si(t)_{old} \cdot \left(1 - \left(\frac{\sum_{i=1}^{n} y_i(t)}{N}\right)\right) \tag{7}$$

$$LSi(t + \Delta t) = LSi(t) + \eta_{LSi} \cdot \left(Si(t)_{new} - LSi(t)\right). \Delta t \tag{8}$$

where, Si is normalized social influence of the worker and LSi is long-term social influence of the worker.

In IFA's third scenario, which is based on the first case in self-confidence model [1], which emphasizes the application of deep learning, there is a portrayal of an individual with a robust personality and strong abilities. These traits are augmented by extensive knowledge and motivation, fostering a positive self-concept in the workplace. This raises the question, *"How do high self-concept and low self-efficacy influence a worker's abilities* **(**Ab**)** *over time?".* As detailed in (5), during training, corrective feedback is administered to rectify the loss function. This is captured in the fixed feedback matrix, projecting the worker's abilities, which are calculated using the learning rate η_{LAb}, as shown in (6).

Understanding the underutilization of abilities in specific tasks due to low self-efficacy, despite a positive overall self-view, can be integrated through the lens of various psychological theories. Bandura's self-efficacy theory [22] is foundational, emphasizing how belief in one's ability to succeed in particular situations influences actions, leading individuals with low self-efficacy in certain areas to avoid tasks requiring those skills. Ajzen's theory of planned behavior [23] extends this idea by suggesting that low self-efficacy (perceived behavioral control) reduces the intention to engage in these tasks. Additionally, Weiner's attribution theory [24] explains how individuals attribute causes to successes and failures; internal attributions for failure in specific tasks can reinforce low self-efficacy, leading to task avoidance. These theories collectively illustrate the dynamic interaction between self-perception, self-efficacy, and behavior, particularly in how low self-efficacy in certain areas can result in the underutilization of abilities, despite an otherwise positive self-view.

For all scenarios of IFA, as shown in Figure 3, feedback is conceptualized as a complex process that affects and is affected by various personal and social factors. The feedback matrix introduces abilities (Ab), Norm motivation (Nm), and social influence (Si) as the input layer, representing external factors that initiate the feedback cycle. These factors impact core aspects such as ability (Ab), norm motivation (Nm), and social influence (Si), which in turn influence knowledge (Kn), performance (Pe), and motivation (Mo) within the endogenous layer. The interactions between these elements lead to Forms of Social persuasion (Sp), which directly shapes an individual's sense of worthiness (Wo). This perceived worthiness has a cascading effect on the long-term psychological constructs of self-esteem (LEs), self-efficacy (LEf), and self-concept (LCo). Through iterative cycles, feedback not only informs and modifies immediate behavior and cognition but also contributes to the long-term development of an individual's self-perception and competencies. To encapsulate the complexities of these interactions, it is necessary to rewrite the equations of the original model as shown in (9)-(13), to ensure the mathematical representation aligns with the complex feedback mechanisms presented.

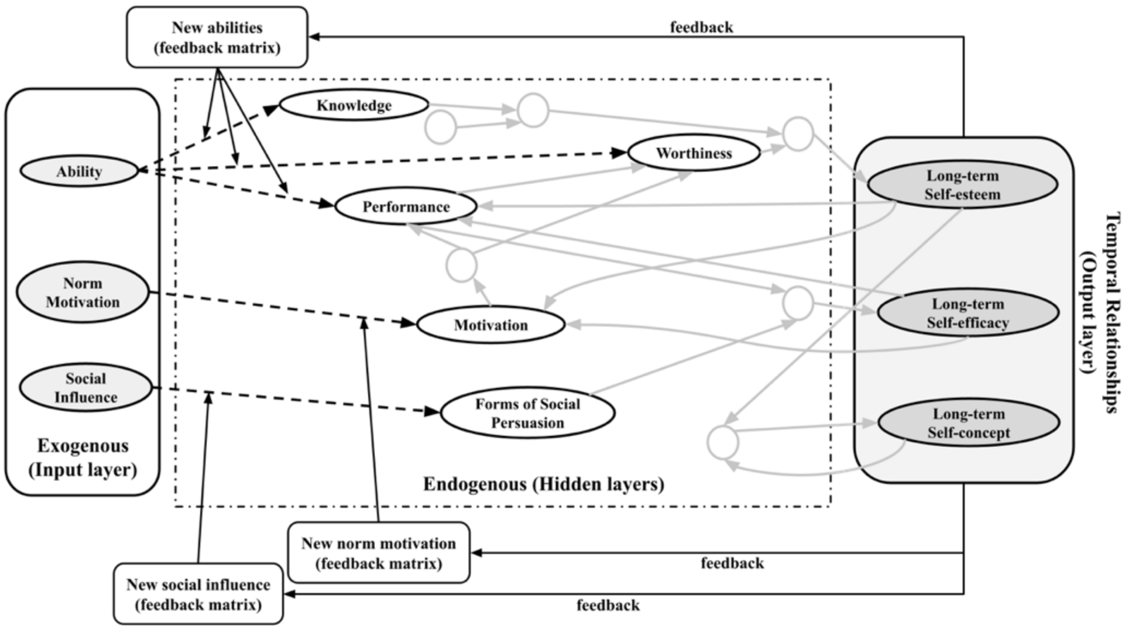


Figure 3. IFA in the self-confidence model for deep learning

$$Mo(t) = \frac{dLNm(t)}{dt}.Nm(t) + (1 - \vartheta_{Mo}).\left(\omega_{Mo}.LEf(t) + \omega_{Mo}.LEs(t)\right) \tag{9}$$

$$Kn(t) = \left(1 - \frac{dLAb(t)}{dt}\right).Ab(t) + \gamma_{Kn}.Ex(t) \tag{10}$$

$$Wo(t) = \delta_{Wo}.\left(\frac{dLAb(t)}{dt}.Ab(t) + \omega_{Wo}.Ef(t)\right) + (1 - \delta_{Wo}).Pe(t) \tag{11}$$

$$Sp(t) = \frac{dLSi(t)}{dt}.Si(t) + \left(1 - \alpha_{Sp}\right).It(t) \tag{12}$$

$$Pe(t) = \frac{dLAb(t)}{dt}.Ab(t) + \omega_{Pe}.LEs(t) + \omega_{Pe}.LEf(t) + \omega_{Pe}.Ef(t) \quad (13)$$

where, ϑ_{Mo} is evaluating the motivation of a worker, ω_{Mo} is connections weights, γ_{Kn} is evaluating the knowledge of a worker, Ex is worker experiences, α_{Sp} is evaluating a worker's social persuasion, It is worker influence tactic, ω_{Pe} is connections weights, and Ef is worker effort. A simulation tool was developed to conduct experiments based on the provided formulas, incorporating IFA. This tool primarily focuses on examining distinct patterns and traces that illustrate the dynamics of self-confidence in relation to the work environment.

5. COMPARISON OF EXPERIMENTS AND EQUILIBRIUM ANALYSIS

In this section, the experiment focuses on applying methodologies outlined in the literature review to observe and analyze the behavior and pattern formation among real workers in various settings as explained in section 3. This experiment is framed within the context of the proposed IFA for enhancing deep learning in workplace self-confidence. The IFA underscores the importance of several theories that contribute to fine-tuning the weight matrix parameters in deep learning algorithms. It becomes essential to understand the long-term impacts of low or high output from the network layers on the input layers. By aligning this analysis with the previously mentioned individuals and scenarios, which are designed to reflect findings from four earlier empirical studies as explained in section 3, a comprehensive understanding emerges. This method facilitates a direct comparison, allowing insights into how theoretical concepts from literature are practically manifested and observed in workplace environments.

The specific settings chosen, reflecting constraints of clarity in proposed IFA for enhancing deep learning in workplace self-confidence, include a time increment (Δt) of 0.3, a mental duration mix time (t_{mix}) set at 800 (analytic of an estimated 13-hour mental workload), initially regulatory rates ($Ab(t)_{new}$, $Nm(t)_{new}$, and $Si(t)_{new}$) maintained at 0.7, and non-zero speed factors (η_{LSi}, η_{LAb}, and η_{LNm}) at 0.3.

Section 4 introduces three scenarios of IFA, tracing the simulation of each scenario and comparing them with the original measures of workplace self-confidence [1]. In the top row of Figure 4, the baseline simulations for self-esteem, self-efficacy, and self-concept are observed, providing a reference for assessing the impact of IFA on workplace self-confidence. These plots serve as a control group against which the enhanced scenarios can be evaluated. Figure 4(a) the top-left graph represents the trajectory of self-esteem in a standard workplace setting without the application of IFA. The gradual increase in levels indicates a natural progression of self-esteem over time. Figure 4(b) the top-center graph illustrates the self-efficacy levels, which show a more moderate increase compared to self-esteem. This suggests that employees' belief in their ability to complete tasks successfully may develop at a different rate than their overall self-esteem. Figure 4(c) the top-right graph displays the self-concept simulation, highlighting a more nuanced development over time. Self-concept, being a broader construct, encompasses both self-esteem and self-efficacy and thus presents a composite growth curve.

Moving to the bottom row, displays the results of the enhanced simulations, indicating the dynamic changes in self-esteem, self-efficacy, and self-concept with the application of IFA: Figure 4(d) the bottom-left graph shows a markedly different trajectory for self-esteem after IFA implementation, with a steeper increase suggesting a significant impact of the intervention. Figure 4(e) the bottom-center graph shows the self-efficacy simulation under IFA conditions. Here, it notices a noticeable improvement in the rate at which self-efficacy levels rise, emphasizing the effectiveness of IFA in expediting self-efficacy development. Figure 4(f) finally, the bottom-right graph presents the enhanced self-concept scenario. It demonstrates a noticeable shift in the curve, indicating an overall boost in the employees' self-concept after the application of IFA strategies. The comparison simulations demonstrate how IFA can enhance and accelerate the components of deep learning associated with self-confidence in the workplace.

The proposed IFA for enhancing deep learning of workplace self-confidence is evaluated through mathematical analysis. Equilibrium or stability points are determined to ensure the model's expected development. The purpose of the mathematical analysis is to identify potential equilibrium values for other variables. When combined, the proposed IFA for enhancing deep learning of workplace self-confidence can be represented as a set of differential equations as (14).

$$\frac{dLAb(t)}{dt} = \frac{dLSi(t)}{dt} = \frac{dLNm(t)}{dt} = 0 \quad (14)$$

Each resulting combination of the stable-state equations for the proposed IFA to enhance deep learning of workplace self-confidence can be rewritten as (15) to (17):

$$LAb = 0 \lor LAb = 1 \lor LAb = Ab \quad (15)$$

$$LSi = 0 \lor LSi = 1 \lor LSi = Si \quad (16)$$

$$LNm = 0 \lor LNm = 1 \lor LNm = Nm \quad (17)$$

Note that by utilizing the other non-dynamic equations, additional evidence regarding the equilibrium conditions of other variables can be uncovered for each selected example and linked to the literature.

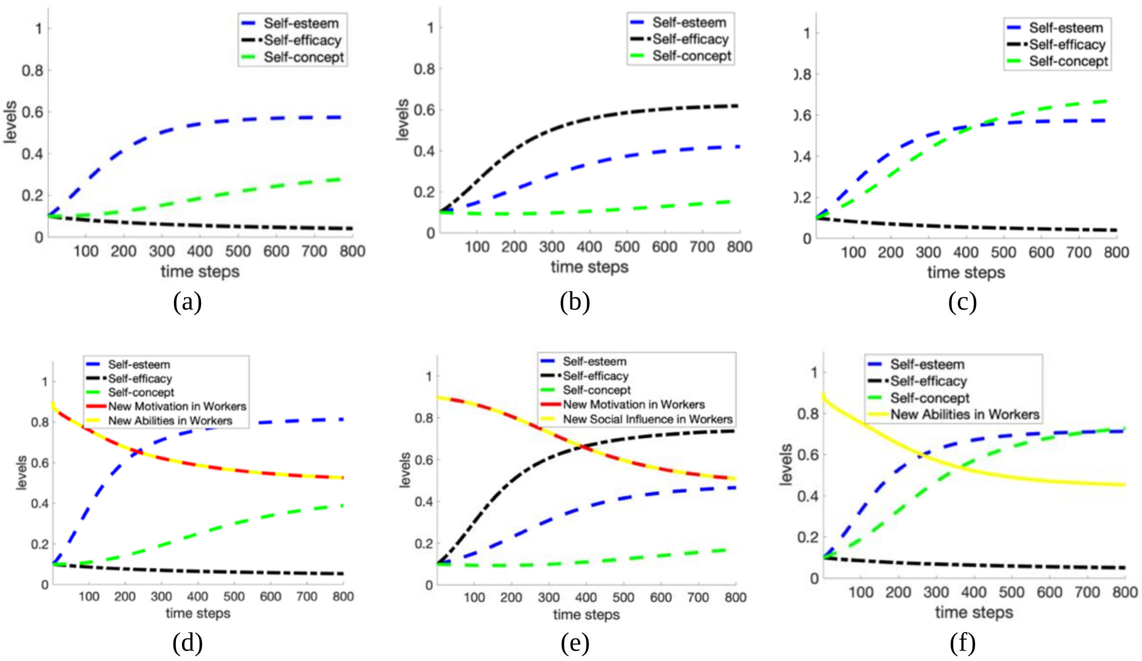


Figure 4. Three scenarios of IFA for enhancing deep learning in workplace self-confidence (a) results of the original self-esteem simulation, (b) results of the original self-efficacy simulation, (c) results of the original self-concept simulation, (d) results of the enhanced self-esteem simulation, (e) results of the enhanced self-efficacy simulation, and (f) results of the enhanced self-concept simulation

a. Case #1: $LAb = 1$

When worker's long-term ability is very high (LAb), work ability was perceived as the worker's personal responsibility. Which could be influenced by both work circumstances and private life (worker's experiences (Ex)). To promote good work ability among workers, it must be understood within it is specific context [25]. According to the equation of worker's knowledge (10):

$$\left(1 - \frac{dLAb(t)}{dt}\right).Ab(t) + \gamma_{Kn}.Ex(t) = 0 \quad (18)$$

Assuming that $LAb = 1$ and $\gamma_{Kn} = 1$:

$$Ab = -Ex \quad (19)$$

Thus, Ab is equal to the negative of Ex. This represents a simple linear relationship between Ab and Ex, as proven in [25].

b. Case #2: $LSi = 0$

When long term worker's social influence (LSi) is very low, the strategies and teleworkers' perceived organizational, worker's influence strategies (It) impact teleworkers (very low social influence) [26]. According to the equation of worker's forms of social persuasion (12):

$$\frac{dLSi(t)}{dt}.Si(t) + (1 - \alpha_{Sp}).It(t) = 0 \quad (20)$$

Assuming that $LSi = 0 \; and \; \alpha_{Sp} = 0$

$$It = 0 \tag{21}$$

Thus, It is equal to the zero. This reprersnts a smple linear relationship between It and Si, as proven in [26].

c. Case 3#: $LNm = 0$

Self-esteem (LEs) scale and self-efficacy (LEf) scale. The results emphasize the mediating role of psychological flourishing between personality traits-self-esteem and self-efficacy and career decision difficulties (such as lack of motivation (LNm)). It also reveals that individuals who are flourishing the most in their lives experience the least difficulty in making career decision. According to the equation of worker's motivation (9):

$$\frac{dLNm(t)}{dt}.Nm(t) + (1 - \vartheta_{Mo}).\left(\omega_{Mo}.LEf(t) + \omega_{Mo}.LEs(t)\right) = 0 \tag{22}$$

Assuming that $LNm = 0, \vartheta_{Mo} = 0 \; and \; \omega_{Mo} = 1$

$$LEf = -LEs \tag{23}$$

Thus, LEf is equal to the negative of LEs. This represents a simple linear relationship between LEf and LEs, as proven in [27].

The proposed IFA for enhancing deep learning of workplace self-confidence was tested in various situations (as demonstrated in proven cases 1, 2, and 3) to assess its alignment with the core concepts of workplace self-confidence. Mathematical analysis was employed to explore feasible equilibrium conditions and compatible cases found in the literature.

6. CONCLUSION

This paper presents a groundbreaking approach to enhancing self-confidence in the workplace by integrating IFA with cognitive agent modeling. The study reveals that IFA, a novel deep learning algorithm, effectively addresses the challenge of credit assignment in neural networks, offering a more biologically plausible and efficient method compared to traditional backpropagation. Through the lens of cognitive agent modeling, the dynamics of self-confidence were explored, self-concept, self-esteem, and self-efficacy among employees, highlighting the intricate interplay of endogenous and exogenous factors in professional environments. The proposed IFA was tested to enhance workplace self-confidence, aligning with core concepts through mathematical analysis. Findings show that IFA significantly improves self-confidence, self-esteem, self-efficacy, and self-concept among employees, suggesting it enhances deep learning and positively impacts workplace psychology. For example, human resource managers play a crucial role in adopting new technologies to enhance employee development and workplace dynamics. This study provides valuable insights for HR managers. By integrating IFA into training programs and cognitive agent modeling, HR managers can boost their data analytic employee self-confidence and job performance. Utilizing this proposed method helps develop effective policies and strategies, fostering a culture of continuous improvement and effective decision-making. This approach offers a cutting-edge method to improve workplace dynamics and align learning processes with complex management principles. The study highlights IFA's potential in enhancing self-confidence analytics in professional settings and opens new research avenues in neural computation and organizational behavior. Future work will compare IFA's effectiveness with cognitive agent modeling and Hebbian learning using self-modeling networks and incorporate physical laws into learning with physics-informed neural networks described by partial differential equations (PDEs).

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BIOGRAPHIES OF AUTHORS

Hareebin Yuttachai is an assistant professor at the Faculty of Humanities and Social Sciences, Prince of Songkla University, Pattani, Thailand. He is an expert in human resource management research, strategic human resource management (SHRM), and business innovation. His specific areas of interest include halal entrepreneurship, personal OKRs, and skill sets for the future workforce. He has published 11 papers in the Scopus database, with 52 citations and an H-index of 5. He previously served as the deputy director of the graduate school office at Phuket Rajabhat University (2023-2024) and is currently on the editorial board of the Phuket Rajabhat University academic journal. He can be contacted at email: Yuttachai.mas@gmail.com.

Billel Arbaoui is currently teaching as a lecturer in the Department of Information and Communication Technology at Rangsit University, Pathumthani, Thailand. He is also a Ph.D. candidate at the School of Computing in Universiti Utara Malaysia (UUM). His research domains encompass modeling, human-computer interaction, and artificial intelligence. He obtained his master's degree in information technology from the UUM, following his bachelor's degree in mathematics and computer science from the University of Blida in Algeria. He can be contacted at email: bill.a@rsu.ac.th.

Yusraw O-manee holds a position as a lecturer in the Department of Public Administration at Phuket Rajabhat University, Phuket, Thailand. Simultaneously, she is pursuing her doctoral studies at the School of Government at Universiti Utara Malaysia (UUM). Her research interests primarily lie in the fields of human resource management and public administration. She holds a master's degree in public management from UUM, which followed her bachelor's degree in liberal arts with a major in English from Walailak University in Thailand. She can be contacted at email: yusraw.o@pkru.ac.th.