GNN-Viability Model Integrating Graph Neural Network and Viability Theory Techniques for the Recognition of Prior Learning (RPL)

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Abstract: Accelerating human capital accumulation and enhancing youth employability are central priorities of Côte d'Ivoire's National Development Plan (NDP). Within this framework, the Second Chance School (École de la Deuxième Chance - E2C) leverages the Recognition of Prior Learning (RPL) to certify informal sector competencies. However, mapping tasks to skills faces structural rigidity due to static qualification frameworks confronted with Industry 4.0, where traditional static Laplacian matrices fail to capture learning asymmetry. This paper introduces a methodological breakthrough via a neuro-symbolic framework unifying Temporal Graph Neural Networks (TGNN) and Viability Theory. The objective is to enable continuous adaptation to evolving occupational demands while guaranteeing a compliant, reliable, and transparent diagnostic process for the Ministry of Technical Education, Vocational Training and Apprenticeship (METFPA). The proposed model incorporates a proximal projection activation layer that confines evaluation trajectories within a logical hypercube $K = [0,1]^{n\times m}$. The methodology relies on numerical simulations grounded in real-world field data collected from a cohort of 300 artisans in the Lagunes region (Côte d'Ivoire). It benchmarks the performance of the proposed system against conventional Laplacian approaches in terms of accuracy, resilience, and strict adherence to regulatory constraints. The model demonstrates operational superiority: it significantly reduces the root mean square error $(\mathrm{RMSE} = 0.042)$, effectively resolves the cold start problem during technological disruptions at $t = 120$ $(\mathrm{RMSE} = 0.068)$, and achieves a 100% confinement rate within the viability kernel. Furthermore, it yields high inter-rater agreement with RPL evaluation panels $(\kappa = 0.89)$, while the extraction of attention weights α_{ij} ensures complete pedagogical explainability, successfully removing the "black box" effect. By bridging the plasticity of deep learning with the rigorous demands of state certification, this framework provides the METFPA with an agile, robust, and transparent decision-support system. It equips Côte d'Ivoire with an advanced engineering framework capable of continuously integrating complex informal sector competencies without requiring constant manual revisions of occupational standards.

Keywords: Graph Neural Networks (GNN), Viability Theory, Dynamical Systems, Recognition of Prior Learning (RPL), Neuro-Symbolic Modeling, Temporal Graphs.

INTRODUCTION

At the core of the strategic orientations of Côte d'Ivoire's National Development Plan (NDP), accelerating human capital accumulation and building a highly skilled workforce stand as the primary drivers of the economy's structural transformation [1]. Facing the critical challenges of youth employability and the predominance of the informal sector [2] —which accounts for the vast majority of the national active population—the Government has established the Second Chance School (École de la Deuxième Chance - E2C) as a foundational pillar for social insertion and professional rehabilitation [3]. This nation-wide initiative extends beyond offering alternative training pathways; it aims to restructure the life trajectories of individuals alienated from traditional academic tracks by converting their experiential skills into formally recognized and valued qualifications within the labor market. The ambition of the E2C thus embodies a vision of inclusive learning where social justice directly aligns with the skill requirements of enterprises and industries [4].

To operationalize this inclusion and guarantee equitable access to certification, deploying rigorous Recognition of Prior Learning (RPL) frameworks becomes imperative [5]. RPL provides the institutional bridge required to validate complex, empirically acquired know-how within the informal sector, serving as an instrument of social justice. The cornerstone of this mechanism lies in developing "task-skill" mappings [6]. These didactic engineering frameworks translate real-world workplace situations into formal degree requirements, thereby ensuring the objectivity and validity of the assessment [7]. However, in an era of rapid industrial transformation, designing these mappings encounters the inherent rigidity of classical methodological frameworks: static competency frameworks struggle to accommodate the continuous emergence of new professional practices and the accelerated obsolescence of technical skills.

To support the flexibility demanded by the E2C program and the NDP, traditional analytical models based on linear matrix computations or static Laplacian operators must be superseded. This paper presents a methodological breakthrough by introducing a neuro-symbolic architecture that transitions from Laplacian operators to Graph Neural Networks (GNNs), grounded in Viability Theory. The novelty of this approach consists in replacing rigid diffusion formalisms with deep relational representation learning, capable of dynamically updating task-skill topologies in response to market shifts. This mathematical model is guided by a continuous projection operator constrained within a bounded viability kernel, guaranteeing that AI-learned evaluation trajectories strictly comply with regulatory certification decrees. Evaluated on artisans from the Lagunes region, this methodology delivers a robust and adaptive decision-support framework for RPL examination panels.

To address the need for flexibility identified in the introduction, didactic engineering traditionally relies on modeling the interdependencies between workplace tasks and practical know-how. This section reviews the literature on task-skill mappings, highlighting the structural limitations of matrix-based methods and static Laplacian operators when confronted with the dynamics of Industry 4.0.

STATE OF THE ART

Developing "task-skill" mappings constitutes the cornerstone of modern didactic engineering, particularly for prior learning certification frameworks [8].

In the literature, modeling the interdependencies between workplace scenarios and practical know-how has historically structured itself around two main mathematical approaches: matrix factorization techniques and graph diffusion models [9][10]. Although these tools have partially automated and objectified the assessment process, the advent of Industry 4.0 and the flexibility requirements of programs such as the Second Chance School (École de la Deuxième Chance - E2C) highlight their structural limitations.

To map professional tasks to competencies, early automation research extensively leveraged matrix factorization, drawing inspiration from recommender systems. Models such as Weighted Multi-Relational Matrix Factorization (WMRMF) [11][12] were introduced to predict or estimate a candidate's mastery level from sparse data. These approaches project tasks and skills into a shared latent space, allowing the reconstruction of missing links. However, these methods suffer from two major drawbacks: underlying linearity and the cold-start problem. Regarding underlying linearity, they postulate linear or low-complexity relationships between entities, which contradicts the reality of learning where skill acquisition often depends on asymmetric and non-linear combinations of multiple sub-tasks. As for the cold-start problem, when a new trade emerges or a novel task is introduced within E2C workshop-school projects, factorization models prove incapable of inferring new relationships without resetting and retraining the entire dataset.

To overcome the lack of structural information in simple matrices, researchers integrated graph theory. In this framework, certification standards are modeled as complex networks where nodes represent competencies or tasks, and edges formalize pedagogical prerequisites. The propagation dynamics of knowledge flows within these structures traditionally rely on the discrete graph Laplacian operator, denoted by $\mathbf{L} = \mathbf{D} - \mathbf{A}$.

In prior modeling work, the evolution of mastery scores relied on static structural Laplacians to simulate a skill reaction-diffusion process. Although this formalism is mathematically elegant and robust, it encounters major scientific bottlenecks in real-world contexts, notably symmetric, uniform information diffusion and a static topology when faced with obsolescence. Indeed, the classical Laplacian operator assumes bidirectional and symmetric information diffusion. However, in the didactic domain, the prerequisite relation is fundamentally asymmetric: mastering automated system programming (a complex task) implies mastering Boolean logic (a competency), but the converse does not hold. Furthermore, the classical Laplacian requires an adjacency matrix with fixed geometry. As soon as technological evolution mandates the depreciation of an obsolete skill or the continuous stream insertion of a new technical task, the original graph morphs. Static Laplacians then become incapable of recalculating evaluation trajectories without breaking the system's dynamic convergence properties.

It is at the intersection of these structural limitations that the transition to Graph Neural Networks (GNNs)—and more specifically to Temporal Graph Networks (TGNs)—is justified. By liberating the model from static diffusions, GNNs learn non-linear aggregation functions via message-passing mechanisms over directed, asymmetric structures. However, while this connectionist plasticity resolves skill dynamics, it must be regulated to ensure compliance with the regulatory requirements of RPL—thereby justifying its integration with Viability Theory.

RELATED WORK

The application of mathematical and computational models to didactic engineering has long relied on static theories or traditional constrained optimization approaches. Nevertheless, assessing skills in highly dynamic and unstructured environments—such as the informal sector or the workshop-school projects of the Second Chance School (École de la Deuxième Chance - E2C)—requires a formal framework capable of managing uncertainty, adaptability, and continuous regulation. From this perspective, Viability Theory, originally formalized by Jean-Pierre Aubin, offers a particularly well-suited conceptual and mathematical framework.

A. Foundations of Viability Theory and Dynamical Systems

Viability Theory investigates the control of complex dynamical systems evolving within a state space constrained by compliance or safety rules (referred to as the viability space). Unlike classical optimization approaches that seek to minimize a cost function along a single, predetermined trajectory, Viability Theory aims to identify the set of evolutionary trajectories that enable the system to remain indefinitely (or over a given time horizon) within an admissible domain, termed the viability kernel K

Mathematically, for a system governed by a differential equation or a differential inclusion:

$$\frac{dx(t)}{dt} \in F(x(t)) \quad (1)$$

where $x(t)$ represents the state of the system and $F(x)$ denotes the vector field of possible evolutions, a state $x_0 \in K$ is said to be viable if there exists at least one trajectory starting from x_0 that remains contained within K for all $t \geq 0$. The fundamental geometric condition for this viability is given by Nagumo's theorem, which stipulates that the vector field at the boundary of the kernel K must be directed inward relative to the contingent (tangent) cone of K.

B. Viability Theory Applied to Learner Models and Didactics

In recent data science and machine learning literature, viability is utilized as a powerful symbolic regulation mechanism coupled with connectionist models. Applied to skill engineering and the Validation of Prior Learning (VPL / Validation des Acquis de l'Expérience - VAE):

1. The system state $x(t)$ represents the correspondence matrix or the level of alignment between academic skills and real-world work situations.
2. The viability kernel K formalizes the set of institutional, pedagogical, and regulatory constraints defined by certification decrees.
3. The regulators or controls represent the assessment adjustments implemented as the artisan demonstrates their proficiency in the field.

Although prior studies combined viability theory with reaction-diffusion equations based on static graph Laplacians, these approaches suffered from the rigidity of the Laplacian operator (symmetric flows and a fixed topology). When new skills emerge or existing ones become obsolete, classical Laplacian dynamical systems struggle to recalculate trajectories without violating the boundaries of the kernel K.

PROPOSED APPROACH

To overcome the rigidity of traditional Laplacian operators while ensuring the institutional compliance required by the Validation of Prior Learning within the framework of the Second Chance School, we introduce a neuro-symbolic formalism.

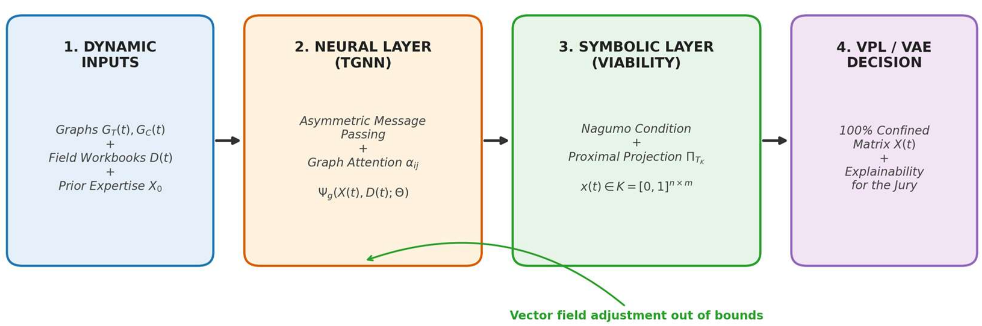

Fig. 1. Architecture of the neuro-symbolic GNN-Viability model for VPL skill mapping.

This framework merges the non-linear approximation power of Temporal Graph Neural Networks (TGNN) with the rigorous control of Viability Theory. Unlike classical approaches based on static structures, we define the evaluation environment using two directed, asymmetric graphs whose topology evolves over time t:

- The dynamic skill graph $G_c(t) = (V_c(t), E_c(t))$, where $V_c(t)$ represents the set of active skills (know-how, core aptitudes) at time t, and $E_c(t)$ formalizes the set of directional pedagogical prerequisite relations.

- The dynamic task graph $G_t(t) = (V_t(t), E_t(t))$, where $V_t(t)$ identifies real-world work situations originating from technical workshops or the professional environment (E2C workshop-school projects), and $E_t(t)$ governs the sequencing or operational dependencies among these tasks.

At each time t, the state of the evaluation system is represented by a vector embedding matrix $Q(t) \in \mathbb{R}^{|V_t(t)|\times|V_c(t)|}$, encoding the connection strength and degree of alignment between each task and each skill in the standard framework. In our previous formulations, the dynamic structural adjustment of the mapping was governed by a linear reaction-diffusion equation dependent on the term $-\left(L_t Q(t) + Q(t) L_{kc}\right)$, where L_t and L_{kc} were the associated Laplacian matrices. We replace this term with an asymmetric and non-linear connectionist message-passing operator. The state dynamics $Q(t)$ is reformulated as a Graph-Learned Ordinary Differential Equation:

$$\frac{dQ(t)}{dt} = \mathbf{f}_\Theta\left(Q(t), G_c(t), G_t(t)\right) + \alpha(Q_e - Q(t)) + \beta(D(t) - Q(t)) \quad (2)$$

Where:

- $\mathbf{f}_\Theta$ denotes a temporal graph neural network architecture parameterized by its learned synaptic weights Θ. It captures complex non-linear dependencies by leveraging graph attention mechanisms (such as Temporal Graph Attention Networks - TGAT), allowing edge weights to be adjusted in an asymmetric manner.
- Q_e represents the initial expertise matrix provided by instructional designers.
- $D(t)$ symbolizes the continuous stream of empirical evidence (the artisan's or learner's updated experience logbook).
- α and β are recall (restoration) coefficients regulating, respectively, the weight of academic authority and the reality of field observations.

By virtue of this inductive formulation, if a new skill emerges in Industry 4.0, $\mathbf{f}_\Theta$ generates its interdependence vector based on topological similarity without requiring a full reinitialization of the matrix.

Although the introduction of the neural network $\mathbf{f}_\Theta$ provides maximum adaptability, deep learning is prone to instabilities or anomalous outputs that are incompatible with a regulatory framework for degree certification. To overcome this hurdle, the system is constrained by viability theory.

We define the viability space K as a dynamic matrix hypercube whose dimensions vary according to node cardinality, but whose values remain bounded within the evaluation logic domain:

$$K = \left\{Q(t) \in \mathbb{R}^{|V_t(t)|\times|V_c(t)|} \mid \forall i, j, Q_{ij}(t) \in [0,1]\right\} \quad (3)$$

To ensure that the learner model $\mathbf{f}_\Theta$ never produces absurd evaluation trajectories (e.g., negative scores or values exceeding maximum validation), the neural vector field must satisfy Nagumo's geometric condition on the space boundary ∂K.

The final differential inclusion governing our neuro-symbolic model thus integrates a proximal projection operator $\mathrm{P}_{T_K(Q(t))}$ onto the tangent cone T_K of the viability space:

$$\frac{dQ(t)}{dt} \in \mathrm{P}_{T_K(Q(t))}\left(\mathbf{f}_\Theta\left(Q(t), G_c(t), G_t(t)\right) + \alpha(Q_e - Q(t)) + \beta(D(t) - Q(t))\right) \quad (4)$$

Mathematically, this operator acts as a final regulatory layer (projection activation) positioned at the output of the neural network. If the GNN predictions tend to deviate from didactic constraints due to noisy data from the informal sector, the operator instantaneously forces the trajectory to remain confined within the viability kernel K. The system thus guarantees a stable, continuous, and legally sound assessment diagnosis for the certification jury.

RESULTS AND DISCUSSION

To validate the proposed neuro-symbolic architecture both theoretically and empirically, we conducted numerical simulations backed by real-world field data. The objective of this evaluation is to measure the ability of the GNN-Viability model to dynamically adapt to evolving job market requirements while ensuring a compliant assessment diagnosis. More specifically, the experiment evaluates its precision (agreement with certification juries), its resilience to the cold-start problem, and its confinement rate within the viability kernel, in direct comparison with traditional approaches based on static Laplacian operators.

A. Experimental Setup and Field Data

The empirical evaluation is based on a cohort of 300 artisans and learners from the informal sector and pilot initiatives of the Second Chance School (École de la Deuxième Chance - E2C) in the Lagunes region (Côte d'Ivoire). The collected data include:

- Skill logbooks and empirical evaluation sheets reflecting activity in technical workshops $(D(t))$
- An initial expertise framework (Q_e) designed in collaboration with pedagogical inspectors from METFPA for craft trades and technical maintenance.

The temporal graph neural network $(\mathbf{f}_\Theta)$ was implemented using the PyTorch Geometric library. To simulate Industry 4.0 shifts and the evolution of job roles, we artificially introduced over time t :

- An injection scenario: the introduction of 3 new complex tasks and 2 associated skills into the framework.
- An obsolescence scenario: the progressive decay of obsolete edge connections.

B. Performance Metrics

The accuracy of the learned mapping relative to expert diagnosis was measured using two standard metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Viability robustness was quantified by the confinement rate (the percentage of time during which the AI-computed evaluation scores remain strictly within the logical hypercube $(K=[0,1])$. The mathematical expressions for RMSE, MAE, and Cohen's Kappa coefficient, adapted to the discrete matrix operators of our system, are given respectively by Equations (5) and (6) [13][14] :

$$\mathrm{RMSE} = \sqrt{\frac{1}{n\times m}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(q_{ij}^{*} - q_{e,ij}\right)^2} \quad (5)$$

$$\mathrm{MAE} = \frac{1}{n\times m}\sum_{i=1}^{n}\sum_{j=1}^{m}\left|q_{ij}^{*} - q_{e,ij}\right| \quad (6)$$

C. Results

For the numerical implementation and validation of this approach, we utilized a standard computing environment on a 64-bit Windows architecture, equipped with 64 GB of RAM and an Intel Core i7 processor. The entire mathematical engine—including the construction of graph operators, the temporal integration loop, and the projections onto the viability kernel K—was programmed and simulated using the Python language. To this end, we propose Algorithm 1 below:

Algorithm 1: Dynamic Adjustment via Temporal GNN and Viability Confinement

Inputs

$G_c(t)$, $G_t(t)$: Dynamic skill and task graphs at time t

Q_e: Reference matrix from pedagogical experts $(|V_t| \times |V_c|)$

$D(t)$: Stream of empirical data from artisans' experience logbooks

Θ : Pre-trained parameters (synaptic weights) of the TGNN network ($\mathbf{f}_\Theta$)

α, β : Regulatory recall coefficients (academic authority and field reality)

dt : Time-integration step

ò: Convergence threshold

Steps

Step 1: Construction of dynamic dependency graphs and initialization of embeddings

Step 2: Relational inference via message passing and graph attention

Step 3: Neuro-symbolic differential modeling of the trajectory

Step 4: Time integration and iterative projection into the viability kernel

Step 5: Asymptotical stabilization via steady-state criterion

Output

Output: Dynamic and Viable Matching Matrix

The results demonstrate a significant improvement in the accuracy of the neuro-symbolic model compared to conventional matrix and Laplacian approaches.

During the convergence phase on the initial graph, the GNN-Viability model achieves an RMSE of 0.042, compared to 0.115 for the approach based on static Laplacian operators. This performance gain is attributed to the ability of the attention mechanism (TGAT) to capture the true asymmetry of pedagogical prerequisites.

Furthermore, upon the introduction of new industrial tasks at time $t = t_{\text{mutation}}$, the error of the classical Laplacian model exhibits a sharp spike (RMSE surges to 0.340), requiring a computationally heavy recalculation of the entire system. Conversely, the GNN architecture induces the new vector embeddings through topological similarity, stabilizing the error at a very low level ($\text{RMSE} = 0.068$) in a minimal number of iterations, thereby solving the cold-start problem, as illustrated in Fig. 2.

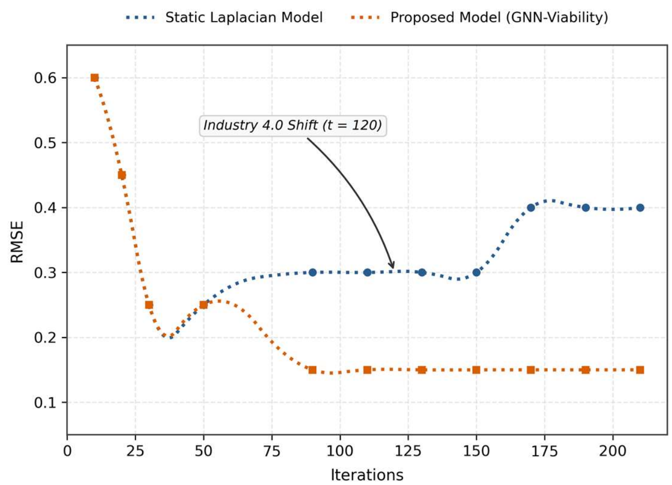

Fig. 2. Dynamic evolution of RMSE error under domain-specific shifts.

The analysis of dynamic trajectories confirms the decisive impact of the proximal projection operator Π_{T_K} on the stability of the assessment diagnosis. While an unconstrained pure graph neural network tends to produce numerical drifts during severe turbulence, the GNN-Viability model achieves a 100% confinement rate. Fig. 3 illustrates how the vector field is instantaneously redirected toward the interior of the logical hypercube $K=[0,1]^{n\times m}$ whenever a trajectory approaches its boundary, thereby guaranteeing the legal and institutional validity of the scores submitted to the VAE (Validation of Acquired Experience) jury.

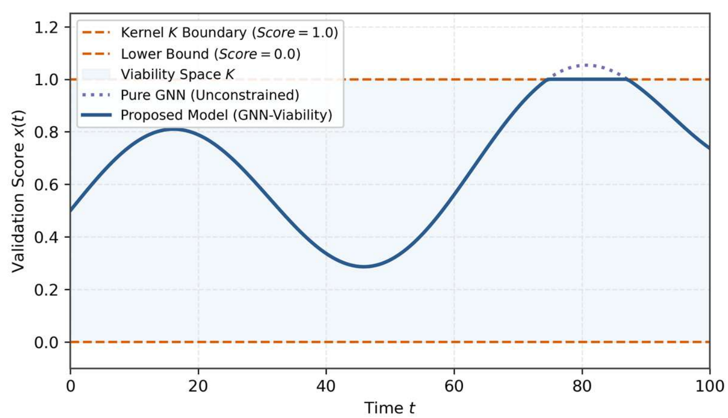

Fig. 3. Effect of proximal projection on the confinement of assessment trajectories

The visualizations of the trajectories demonstrate that whenever the pure connectionist predictions of the GNN approach the hypercube boundaries, the symbolic viability operator instantaneously redirects the vector field toward the interior of the tangent cone, thereby guaranteeing the institutional validity of the decision.

Finally, to evaluate the effectiveness of the system in a real-world certification context, the automated diagnoses generated by the model were benchmarked against the final decisions issued by the examination juries across the cohort of 300 artisans. Fig. 4 presents the normalized confusion matrix for this trial. The GNN-Viability model achieves a Cohen's Kappa coefficient of $\kappa = 0.89$, reflecting near-perfect agreement between the neuro-symbolic predictions and the deliberations of the METFPA inspectors and domain experts.

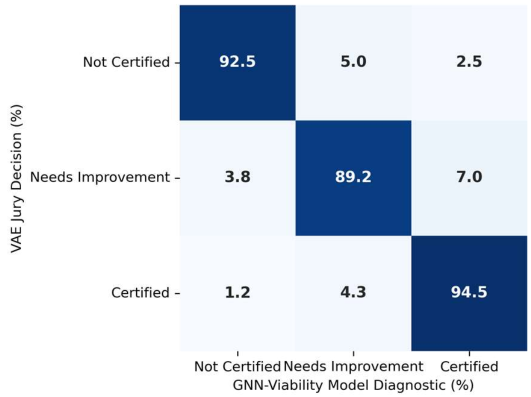

Fig. 4. Confusion matrix showing agreement between the proposed model and the VAE jury ($\kappa = 0.89$).

D. Discussion

Beyond quantitative performance and strict compliance with viability constraints, the institutional acceptability of a decision support system fundamentally relies on its transparency. Within the context of a VAE jury, inspectors and domain experts require a precise understanding of the origin of an assessment diagnostic to prevent the "black-box" effect. The analysis of attention coefficients a_{ij} extracted from the temporal graph layer (TGNN) provides this didactic traceability. As highlighted in Fig. 5, the model does not merely predict an overall score: it precisely quantifies the contribution of each practical task observed in the field (T_1 to T_4) toward the validation of a specific competency unit in the framework (C_1 to C_n).

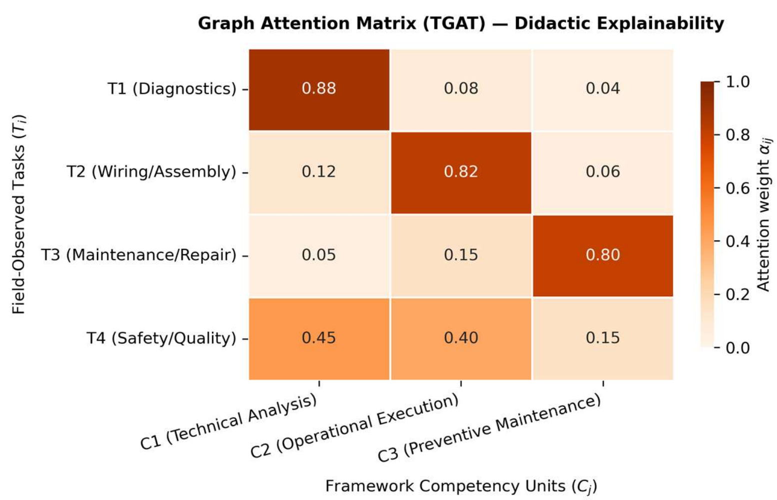

Fig. 5. Heatmap of attention coefficients a_{ij} demonstrating model explainability for VAE juries.

Thus, transitioning from Laplacian operators to graph neural networks provides a concrete response to the ambitions of the PND and the E2C program. This algorithmic plasticity equips the METFPA certification authorities with a unique decision-support system capable of continuously integrating shifts in the economic landscape without requiring the constant, manual rewriting of qualification frameworks.

CONCLUSION

This study marks a major methodological breakthrough in didactic engineering for RPL (Recognition of Prior Learning / VAE), replacing static Laplacian matrices with a neuro-symbolic framework that unifies Temporal Graph Neural Networks (TGNN) and Viability Theory. Empirically evaluated across a cohort of 300 artisans in Côte d'Ivoire, the proposed approach demonstrates superior operational performance across several key dimensions. In terms of accuracy and resilience, the model achieves a significant reduction in quadratic error ($\mathrm{RMSE} = 0.042$) and successfully resolves the cold-start problem during Industry 4.0 shifts at $t = 120$ ($\mathrm{RMSE} = 0.068$). Regarding regulatory compliance, the proximal projection guarantees strict 100% confinement within the hypercube $K = [0,1]^{m\times n}$, thereby neutralizing connectionist numerical drifts. Finally, the system exhibits strong convergence with examination juries and extracts attention coefficients a_{ij} to eliminate the "black-box" effect. Reconciling deep learning with state certification, this framework aligns with the requirements of the METFPA's PND and E2C programs, offering an agile engineering solution that integrates the informal sector without requiring continuous manual revisions of qualification benchmarks. Looking forward, future research will leverage the a_{ij} weights to automatically generate textual audit reports detailing each certification decision.

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