

PAPER

Towards a Viability Approach for the Development of Task-Skill Mappings for the Validation of Prior Learning

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ABSTRACT

Inclusive learning aims to guarantee equitable access to educational opportunities by validating competencies acquired across diverse contexts. In Côte d'Ivoire, where a major share of the active population operates within the informal sector, the Validation of Prior Learning (Validation des Acquis de l'Expérience – VAE) constitutes a critical lever for certifying these skills. However, its operational implementation remains complex due to cumbersome evaluation procedures and the rigidity of certification frameworks. This paper proposes an innovative dynamic systems approach rooted in viability theory to automate and optimize the design of the “task-skill” mappings essential to VAE. By leveraging graph Laplacian operators and differential inclusions, this method models the propagation of knowledge flows within a bounded viability kernel. Experimental validation conducted on a cohort of 300 artisans from the Lagunes region demonstrates the robustness of the model: the stabilized profiles achieve high topological congruence with the official CQP (Professional Qualification Certificate) framework, yielding a Jaccard similarity index of 0.92 and a Cohen's Kappa coefficient of 0.84, while ensuring rapid asymptotic convergence within 150 iterations. The results confirm that this viability approach improves the reliability of didactic diagnostics and reduces the temporal overhead of assessment sessions, thereby facilitating certification access for individuals from informal backgrounds and mitigating educational inequalities. Moving forward, this adaptive model paves the way for hyperparameter self-calibration and sectorial transposition to other evolving professional fields.

KEYWORDS

viability theory, dynamic systems, task-skill mapping, validation of prior learning (VAE), graph laplacian operators, inclusive learning

1 INTRODUCTION

Inclusive learning represents a strategic framework designed to foster equity in access to educational and training opportunities [1] [2]. It is grounded in the foundational principle of ensuring that every individual, regardless of their background,

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experience, or track record, has the opportunity to acquire recognized and valued competencies [3] [4]. In Côte d'Ivoire, where a significant portion of the active population operates within the informal sector [5], inclusive learning takes on paramount relevance [6]. It highlights the urgent need to design adaptive educational systems capable of recognizing and validating competencies derived from non-formal environments, thereby enhancing inclusion and equity within the national educational system.

The Validation of Prior Learning (VAE) aligns with this dynamic as an innovative instrument to promote educational inclusion [7]. It enables the certification of competencies acquired through professional, personal, or associative experience, thus offering a qualification pathway for individuals frequently marginalized by formal training systems [8]. By facilitating the recognition of practical know-how and expanding access to vocational certifications, VAE serves as a significant lever to alleviate educational disparities and strengthen social equity.

However, the implementation of VAE presents substantial challenges. Educational stakeholders encounter significant bottlenecks related to the complexity of administrative procedures and the inherent assessment processes of prior learning validation [9]. These hurdles limit the efficiency and impact of VAE, thereby undermining its contribution to inclusive learning. Furthermore, the construction of “task-skill” mappings represents a cornerstone in structuring VAE certification standards. These mappings, which establish correspondences between tasks performed in a professional setting and their underlying competencies, are crucial to ensuring the relevance and objectivity of the validation processes [10]. Yet, their design remains intricate, demanding a granular understanding of market needs, close alignment with socio-professional stakeholders, and the application of a rigorous methodology. In this context, delivering optimized VAE tools is essential to improve learning quality and foster a more inclusive education.

To address these challenges, this paper introduces a viability-based approach for generating task-skill mappings. Inspired by optimization paradigms and compatibility models, this approach aims to establish a systematic methodology to link tasks to competencies within complex professional environments. This work adopts an interdisciplinary perspective, integrating graph and matrix theories to model task-skill interactions while leveraging advancements in educational sciences. The following section reviews methodological frameworks from the literature regarding task-skill mapping development. Special emphasis is placed on adaptive mapping models engineered to efficiently meet the requirements of VAE systems.

2 STATE OF THE ART

Numerous studies have underscored the significance of task-skill mapping tools in the cognitive assessment of learners [11] [12]. These tools remain a central focus in academic research as they streamline curriculum revision, thereby enhancing learner performance. In the literature, the development of task-skill mappings is primarily categorized into two major paradigms: traditional (manual) methods and automated methods.

Traditional methods rely on manual task analyses, utilizing graphs to illustrate the relationships between tasks and underlying competencies [13] [14]. These approaches provide a granular understanding of the processes, although they are notoriously time-consuming and prone to human bias. Within this context, Abderrazak Boumane et al. [15] discuss methods to identify required skills within competency management frameworks, specifically referencing the ISO 9000 (2000) standard, and propose a structured workflow to conduct this identification effectively. Following a similar workflow, Gono et al. [16] proposed a methodology for

task-skill mapping design tailored to the Ivorian educational context. This framework leveraged guidelines and curricula from the Ministry of National Education and Literacy (MENA) to map tasks against underlying competencies, establishing what is known as the Experts' Q-Matrix. Unfortunately, expert subjectivity can introduce a discrepancy between the candidate's actual field competencies and the expectations delineated in the mapping, hindering objective validation. Moreover, the non-linear or atypical career pathways of certain VAE candidates often fail to align with expert-defined mappings, which are typically designed for standard contexts or formalized curricula.

Conversely, automated approaches leverage computational models and algorithms to generate task-skill mappings more efficiently, exploiting large volumes of data while mitigating the subjective biases inherent in manual methods. In this domain, Wenbin Gan and Yuan Sun [17] introduced the PQRLKA model, which captures interactions between learners and questions using a long short-term memory (LSTM) recurrent neural network. However, this task-skill mapping is inferred within a purely static framework. To address this limitation, Liu et al. [18] developed the TATD-HER method, a curriculum learning approach combining explicit and implicit mechanisms to guide learning effectively. This method tackles the problem of manipulation skill acquisition in complex, multi-step tasks by relying on a structured learning progression from simple to complex tasks. This process mirrors the VAE pipeline, where candidates sequentially structure and articulate their experiences to demonstrate proficiency. Much like the TATD-HER approach, VAE can be enriched by explicit mechanisms (experience analysis) and implicit mechanisms (continuous acquisition of transferable skills) to better highlight prior learning. Nonetheless, while highly effective for specific tasks, this method requires calibration for higher-order complexities or distinct domains.

From this perspective, Sun et al. [19] proposed the Weighting-based Student Exercise Matrix Factorization (Wse-MF) model, introducing explicit weighting based on learner capability and exercise difficulty, along with a loss function incorporating these weights to optimize prediction quality. Compared to benchmark models such as DINA, kNN, PMF, PMF-CD, and fuzzyCDF, Wse-MF exhibits significant improvements in accuracy and error reduction (MAE and RMSE). Recently, Gono et al. [20] [21] introduced the WMRMF and *Sk*-WMRMF models as alternatives for mapping generation. However, these suffer from high parameter dependency and an inability to accommodate the non-linearity of VAE pathways. To overcome these hurdles, viability models emerge as a highly relevant alternative due to their capacity to guarantee system resilience in the face of dynamic changes. Consequently, the objective of this study is to transcend these limitations by proposing a viability-based dynamic framework capable of objectively supporting skill assessment.

3 VIABILITY THEORY

This work integrates viability theory to deliver a continuous, structural mathematical modeling of how experiential learning evolves over time. The goal is to move beyond static paradigms by treating the candidate's profile as a dynamic state flow constrained by the logical structures of the certification standard (prerequisites and pedagogical consistency).

3.1 Continuous dynamic system modeling

Let $I = \{i_1, i_2, \dots, i_n\}$ be the set of n tasks (professional items) and $KC = \{kc_1, kc_2, \dots, kc_m\}$ be the set of m skills. The task-skill mapping at time t is modeled by the matrix state

variable $q_{j,k}(t) \in [0,1]$. Each element $Q(t) \in \mathbb{R}^{n \times m}$ quantifies the dynamic degree of adequacy between the candidate's practical experience and the skill kc_k through the task i_j . The time evolution of the state matrix $Q(t)$ is governed by the following diffusion-reaction differential equation [22]:

$$\frac{dQ(t)}{dt} = -L_i Q(t) - Q(t) L_{kc} + \alpha(Q^* - Q(t)) + \beta(D(t) - Q(t)) \quad (1)$$

Where the structural operators and parameters are defined as follows:

- $L_i \in \mathbb{R}^{n \times n}$ is the Laplacian matrix associated with the task graph (I). It encodes the connectivity and sequential scheduling of evaluation situations. It is defined by $L_i = D_i - A_i$, where A_i is the task adjacency matrix and D_i is the diagonal matrix of their degrees. The term $-L_i Q(t)$ propagates mastery scores via diffusion along interconnected tasks.
- $L_{kc} \in \mathbb{R}^{m \times m}$ is the Laplacian matrix associated with the competency graph (KC), defined by $L_{kc} = D_{kc} - A_{kc}$, where A_{kc} is the adjacency matrix of cognitive prerequisites and D_{kc} is the associated diagonal matrix. The term $-Q(t) L_{kc}$ ensures smoothing and validation consistency based on conceptual dependencies (upstream competencies feeding into downstream competencies).
- $Q^* \in \mathbb{R}^{n \times m}$ denotes the stable reference matrix established a priori by experts (target certification framework or theoretical task-competency mapping).
- $D(t) \in \mathbb{R}^{n \times m}$ represents the real-time observation data matrix, reflecting empirical evidence derived from the candidate's experience logbook or assessments.
- $\alpha > 0$ is the recall coefficient (drift force) pulling the system toward the theoretical expertise framework Q^* .
- $\beta > 0$ measures the assimilation rate of real data, governing the model's sensitivity to the tangible evidence provided by the candidate.

3.2 Viability constraints and trajectory projection

To guarantee a strict pedagogical interpretation, validation scores must be confined within logical bounds. We define the viable admissible set K as the matricial unit hypercube:

$$K = \{Q \in \mathbb{R}^{n \times m} \mid q_{ij} \in [0,1], \forall i, j\} \quad (2)$$

Unlike classical discrete approaches, the viability framework regulates the system dynamics so that the state trajectory never escapes K . The constrained dynamic system is modeled via the differential inclusion leveraging the projection operator Π onto the tangent cone to K at point $Q(t)$ [23]:

$$\frac{dQ(t)}{dt} = \Pi_K(-L_i Q(t) - Q(t) L_{kc} + \alpha(Q^* - Q(t)) + \beta(D(t) - Q(t))) \quad (3)$$

Computationally, for each component (j, k), this operator applies the following projection rules during numerical integration:

$$\text{If } q_{j,k}(t) = 0, \text{ then } \frac{dq_{j,k}(t)}{dt} = \max\left(0, \frac{dq_{j,k}(t)}{dt}\right) \quad (4)$$

$$\text{If } q_{j,k}(t) = 1, \text{ then } \frac{dq_{j,k}(t)}{dt} = \min \left(0, \frac{dq_{j,k}(t)}{dt} \right) \quad (5)$$

This mathematical formulation guarantees that competency scores never diverge toward incoherent values, yielding a robust, stable diagnostic framework that is perfectly interpretable from a pedagogical standpoint

4 EXPERIMENTAL VALIDATION

This section details the experimental validation of the viability approach for task-competency mapping generation. To ground our mathematical model in actual vocational practices, we apply our methodology to the real-world context of vocational training in Côte d'Ivoire.

4.1 Design of the expert reference matrix Q_e

The experimentation relies on the official General Mechanics curriculum from the Ivorian Ministry of Technical Education, Vocational Training, and Apprenticeship (METFPA), targeting the Professional Qualification Certificate (CQP). The curriculum is structured around interconnected competency units. To calibrate our model against the certificate's requirements, we formalized the prerequisite pathways for mechanical production and maintenance modules: statics, kinematics, strength of materials, and blueprint reading. For algorithmic clarity, each vocational competency from the framework is operationalized and treated as a specific knowledge component denoted by the KC formalism. Table 1 provides an excerpt of these codified competencies.

Table 1. Excerpt of knowledge components (KC) from the CQP standard

Unit 1: Technical Diagnosis and Analysis of Mechanical Systems	
$KC001$	Identify and catalog external forces acting on a stationary mechanical system.
$KC002$	Apply the Fundamental Principle of Statics (PFS) to determine support reactions.
$KC003$	Model a fixed constraint or simple support for a mechanical transmission shaft.
$KC004$	Distinguish simple stresses in a beam (Tension, Compression, Shear, Torsion).
$KC005$	Calculate normal tensile stress in a component subjected to an axial force.
...	...
Unit 2: Execution of Corrective Maintenance and Reconditioning Operation	
$KC062$	Locate components of a mechanical sub-assembly on an industrial assembly blueprint.
$KC0634$	Decode geometric specifications (circularity, coaxiality, and parallelism tolerances).
$KC064$	Determine the trajectory and velocity vector of a point belonging to a solid in motion.
$KC065$	Model standardized kinematic joints (ball-and-socket, slider, pivot) using wrench (torseur) tools.

Based on this architecture, precedence constraints are encoded as graphs to generate the task (L_t) and competency (L_{kc}) Laplacian matrices. This mathematical step

is vital to verify the prerequisite tree and ensure that every state trajectory is properly confined within the viability kernel K , which defines the admissibility space for certification. To illustrate the topology of these structural interdependencies derived from expert knowledge, Tables 2 and 3 show excerpts of the binary encoding of these networks. Table 2 formalizes the directive flow of conceptual prerequisites, while Table 3 outlines the sequential chaining of evaluation tasks.

Table 2. Excerpt of the competency adjacency matrix (A_{kc})

	kc_1	kc_2	kc_3	kc_4	kc_5	kc_6	kc_7	kc_8
kc_1	0	1	1	0	0	0	0	0
kc_2	0	0	0	1	1	0	0	0
kc_3	0	0	0	1	0	0	1	0
kc_4	0	0	0	0	1	1	1	0
kc_5	0	0	0	0	0	1	0	0
kc_6	0	0	0	0	0	0	1	0
kc_7	0	0	0	0	0	0	0	0
kc_8	0	1	1	0	0	0	0	0

A value of 1 indicates that the row competency is a mandatory prerequisite for the column competency

Table 3. Excerpt of the task adjacency matrix (A_t)

	q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8
q_1	0	1	1	0	0	0	0	0
q_2	0	0	0	1	1	0	0	0
q_3	0	0	0	1	0	0	1	0
q_4	0	0	0	0	1	1	1	0
q_5	0	0	0	0	0	1	0	0
q_6	0	0	0	0	0	0	1	0
q_7	0	0	0	0	0	0	0	0
q_8	0	1	1	0	0	0	0	0

4.2 Generation of the performance matrix $D(t)$

Once the ontological architecture and structural constraints are set a priori by the reference matrix, validating the viability model requires longitudinal empirical data input. This involves confronting institutional prescriptions with real field trajectories to assess dynamic alignment. The evaluation sample for this study comprises 300 candidates originating from informal backgrounds in the Lagunes region (Abidjan). The various validations achieved by these candidates during practical scenarios, along with findings from a rigorous audit of their professional evidence logs, were aggregated to construct the dynamic empirical performance matrix, denoted as $D(t)$. To capture the full non-linearity and richness of the competencies “in action” developed on the job by these artisans, these field data serve as a major exogenous

information source. Within the viability model, they drive the mathematical assimilation term—expressed as $\beta(D(t) - Q(t))$ —thereby introducing exogenous forcing variables into our reaction-diffusion differential system to continuously calibrate the system's transient state against field realities. Granular evaluation of task-competency interactions was operationalized using a criterion-referenced observation grid deployed across the cohort. For each CQP unit, the collection architecture is structured around the three canonical and standardized phases of the VAE process:

- **Phase I:** Audit of folder admissibility and documentary evidence accumulated during professional practice.
- **Phase II:** Direct observation of technical behavior and manipulation skills during a practical task execution on the technical floor.
- **Phase III:** Structured elicitation interview conducted by the expert jury immediately following the performance.

The raw data thus collected undergo binary encoding (0: Not Acquired, 1: Acquired), reflecting mastery thresholds, before being continuously projected into the viability hypercube $[0, 1]$. Table 4 illustrates an excerpt of the encoding formalism for the temporal performance flow $D(t)$ recorded for a typical candidate across the three evaluation phases.

Table 4. Excerpt of the empirical performance temporal flow $D(t)$ for a typical candidate

	Task	Phase 1	Phase 2	Phase 3	$Di(t)$
S_1	q_1	1	1	1	[1,1,1]
S_2	q_2	0	1	0	[0,1,0]
S_3	q_1	0	1	0	[1,1,1]
S_4	q_6	1	1	1	[0,1,1]
S_5	q_8	0	1	1	[0,0,0]
S_6	q_{10}	0	0	0	[1,0,1]
S_7	q_{12}	1	0	1	[1,1,1]
S_8	q_1	1	1	1	[1,1,1]

4.3 Evaluation metrics

To assess the relevance and behavior of our dynamic systems approach, we exploit two complementary metric categories:

- Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are utilized to quantify the speed and quality of convergence of the transient state matrix $Q(t)$ toward its final steady state Q^* . These metrics gauge the numerical stability of the dynamic system during temporal integration.
- Cohen's Kappa similarity index is introduced to determine the degree of structural divergence between the expert reference matrix Q_e (initial condition) and the stabilized mapping Q^* (equilibrium state). This topological gap allows for pinpointing the specific (competency, task) pairs where the learner's actual trajectory significantly deviates from theoretical expectations, thus isolating critical zones that warrant in-depth interpretation by METFPA pedagogical experts.

The expressions for the RMSE, MAE, and Cohen's Kappa metric, adapted to the discrete matrix operators of our system, are given by equations (6), (7), and (8), respectively [24][25]:

$$RMSE = \sqrt{\frac{1}{n \times m} \sum_{i=1}^n \sum_{j=1}^m (q_{ij}^* - q_{e,ij})^2} \quad (6)$$

$$MAE = \frac{1}{n \times m} \sum_{i=1}^n \sum_{j=1}^m |q_{ij}^* - q_{e,ij}| \quad (7)$$

$$\kappa = \frac{P_o - P_e}{1 - P_e} \quad (8)$$

$$\text{Where: } P_o = \frac{1}{n \times m} \sum_{i=1}^n \sum_{j=1}^m \mathbb{I}(q_{e,ij} = \mathbb{I}(q_{ij}^* \geq \tau))$$

$$\text{And } P_e = P_{\text{expert}} \cdot P_{\text{model}} + (1 - P_{\text{expert}}) \cdot (1 - P_{\text{model}})$$

P_o represents the fraction of (competency, task) pairs for which the expert reference (Q_e) and the stabilized profile generated by the model (Q^*) achieve perfect agreement regarding the presence or absence of a pedagogical anchoring. P_e is computed derived from the marginal probabilities of both matrices.

5 RESULTS AND DISCUSSION

5.1 Experimental results

For numerical implementation and validation, we leveraged a standard 64-bit Windows computational environment equipped with 64 GB of RAM and an Intel Core i7 processor. The entire mathematical engine, including graph operator construction, the temporal integration loop, and projections within the viability kernel K , was programmed and simulated in Python via Algorithm 1:

Algorithm 1: Dynamic Profile Evolution Under Viability Constraints

Inputs

Q_e : Expert reference matrix
 A_{kc} : competency adjacency matrix
 A_t : task adjacency matrix
 $D(t)$: normalized real evaluation log flow

Step 1: Dependency graph construction and degree computation (D_{kc} and D_t)

Step 2: Generation of Laplacian operators (L_{kc} and L_t)

Step 3: Differential modeling of the trajectory. $\frac{dQ(t)}{dt}$

Step 4: Temporal integration and iterative projection into the viability kernel. $K = [0, 1]$

Step 5: Asymptotic stabilization via steady-state criteria $\left(\frac{dQ(t)}{dt} \rightarrow 0\right)$

Output: Q^* Optimized and stabilized task-competency mapping of the candidate.

The trajectories of the RMSE and MAE indices are documented in Table 5.

Table 5. Residual error evolution during temporal integration

Iterations (t)	RMSE	MAE	System State
Initialization (t_0)	0.584	0.492	Initial configuration ($Q(t_0) = Q_e$)
Transient Phase (t_{10})	0.312	0.254	Transient state – Active diffusion
Confinement (t_{60})	0.145	0.098	Confinement within the viability kernel K
Asymptotic Regime (t_{100})	0.042	0.021	Convergence towards steady state
Steady State (t_{150})	0.003	0.001	Asymptotic stabilization achieved $\frac{dQ(t)}{dt} \rightarrow 0$

The results in Table 5 demonstrate a monotonic and rapid decay of both root mean square and absolute errors. At t_0 , the gap reflects the distance between the theoretical expert hypothesis and the raw field validation flow $D(t)$. As the structural Laplacian operators (L_r and L_c) activate, the system smooths out anomalies. Reaching an infinitesimal threshold by 150 iterations confirms the approach's numerical stability. This behavior proves that the projection operator effectively confines learning trajectories within the viable hypercube, preventing mathematical divergence.

Following asymptotic stabilization, the optimized mapping matrix was macroscopically compared against the expert configuration Q_e using the Jaccard similarity index (J), yielding a score of 0.92. Achieving a near-unitary coefficient confirms a remarkably high structural homomorphy between the dynamic-inferred mapping and the initial ontology defined by METFPA didacticians. This proves that continuously integrating field data flows from Lagunes region learners does not corrupt the integrity of the official CQP general mechanics standard. Rather, it rigorously validates its underlying structure while demonstrating the viability model's ability to assimilate field learning without compromising institutional mandates.

At a microscopic scale, the dual task-competency interactions evaluated via Cohen's Kappa (κ) converged to 0.84. According to the Landis and Koch scale, this denotes a "almost perfect" level of structural agreement.

5.2 Discussion

The cross-analysis of macroscopic ($J = 0.92$) and microscopic ($\kappa = 0.84$) metrics confirms the relevance of the developed viability model. Beyond numerical performance, these results yield major theoretical and practical implications at the intersection of educational sciences and applied computer science.

The high structural fit proves that field data flows do not destabilize the degree architecture (CQP). However, the core strength of the model lies in its capacity to capture and isolate non-linear disruptions summarized by local singularities ($\kappa_{local} < 0.4$). For instance, a candidate showing mastery of technical diagnosis without validating the Fundamental Principle of Statics provides a remarkable empirical illustration of the conceptualization-in-action theory in didactic engineering. Among informal artisans in Abidjan, competence is constructed "in act" through repetitive work scenarios driven by physical intuition and empirical transmission, bypassing formal mathematics or traditional didactic transposition. The computational model validates the existence of alternative cognitive structures that remain invisible to traditional academic exams but are fully operational on the technical floor.

Conversely, singularities related to graphical decoding (blueprint reading) highlight a didactic bottleneck caused by graphic abstraction. It confirms that for this demographic,

moving from the physical realm to the symbolic world (standardized geometric specifications) causes a severe cognitive load rupture. This suggests that within VAE contexts, assessment of such knowledge should not fixate on formal tools but rather on the candidate's capacity to operationalize geometric tolerances directly onto the material.

Computationally, continuous dynamic systems coupled with viability theory surpass the limitations of classical predictive learning models. Traditional approaches suffer from two major biases in VAE settings: they require massive training data volumes (seldom available in the informal sector), and they freeze the learner's profile in a static state. The proposed model resolves these bottlenecks through two innovative mechanisms:

- By utilizing graph Laplacian operators, the model avoids unconstrained statistical regression, forcing the flow of competencies to follow the logical tree of professional prerequisites. The rapid monotonic decay of RMSE and MAE validates this computational efficiency.
- By confining the state trajectory within the hypercube $K = [0, 1]$, the model eliminates any risk of numerical instability or outliers, providing robust convergence even when faced with noisy or incomplete field data.

6 CONCLUSION

This study introduces a dynamic systems approach based on viability theory to tackle the automation of task-competency mapping within VAE systems. This framework relies on differential inclusions governed by graph Laplacian operators. It exploits three structural relationships—the competency prerequisite network, the sequential task network, and the expert reference matrix—to continuously project empirical field performances into a bounded viability kernel. An experimental study on a dataset from 300 informal artisans demonstrated that our approach achieves high topological congruence with the official framework ($J = 0.92$, $\kappa = 0.84$). This confirms its accuracy and highly discriminative capability for competency discovery and diagnostic support within vocational certification frameworks. Future work involving sectorial transpositions to explore various graph topologies and implementing optimization methods for hyperparameter self-calibration will further refine the model's generalizability and resilience.

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