Data-Driven Modeling of Employee Performance Using Self-Organizing Maps and Kinematic Models

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Abstract: The employee performance evaluation and optimization is a key objective for modern organizations, where decision making in human resource management must be supported by robust analytical methods. This study proposes a modeling framework based on the integration of Self-Organizing Maps (SOMs) and kinematic models (kinMods) for the analysis and dynamic simulation of the employee performance under different managerial scenarios. SOMs are employed for classifying the employees according to their skills, performance, and potential, thereby identifying latent patterns in the team structure. In addition, the kinMod enables the simulation of managerial scenarios - such as promotions, restructuring, or the departure of key employees - and the assessment of their impact on organizational cohesion and efficiency over time. The experimental results, illustrated by the correlation analysis, employee clustering outcomes, and dynamic simulations, confirm the usefulness of the proposed methodology for reducing subjectivity in human resources assessment and providing an objective decision support tool. The integration of SOMs and kinMods thus provides a transferable methodological framework with potential applications in HR analytics and organizational management.

Keywords: Adaptive topological learning, Kinematic modeling, Employee performance analysis, Human resource analytics, Data-driven decision support.

1. Introduction

Employee performance is a central factor for the success and competitiveness of modern organizations, directly influencing productivity, innovation capacity, and talent retention (Boxall & Purcell, 2016; Wright & Ulrich, 2017). Despite its importance, performance assessment and management often rely on traditional methods -questionnaires, annual evaluations, or isolated quantitative indicators - that do not capture the complex dynamics and real interdependencies within organizational teams (Campbell & Wiernik, 2015; Stepanić et al., 2025). Such methods tend to be static and susceptible to subjectivity, reducing the accuracy of human resources decisions.

This problem becomes evident in situations where organizations must make strategic decisions regarding promotions, restructuring, or succession planning in environments characterized by volatility and uncertainty. In these contexts, the lack of robust analytical and simulation-based tools can lead to the loss of valuable employees, skill imbalances, and a decreased collective performance over time.

To address these challenges, the literature has explored a number of analytical methods. Self-Organizing Maps (SOMs), introduced by Kohonen (2001), have been used for classifying complex data and identifying hidden patterns and have been applied in various fields, including organizational performance analysis (Chen & Kuo, 2019). A SOM allows the visualization and segmentation of employees based on performance, skills, or potential, but its limitations lie in its static nature: the method cannot simulate the long-term effects of managerial decisions.

In parallel, kinematic models (kinMods), originally developed in the fields of biomechanics and robotics (Mao et al., 2026), describe the dynamics of interdependent systems and provide a formal framework for modeling temporal evolution. More recent studies (e.g., Liu et al., 2025; Shafie et al., 2024) illustrate the extension of such models to complex adaptive systems, opening possibilities for organizational-level applications.

By modeling employee relationships and team interdependencies, kinMod offers the possibility of simulating "what if" scenarios: what effects does a team leader promotion have, how does performance change if a key employee leaves the organization, or how does team cohesion evolve after a restructuring? However, the application of kinMod in the field of human resources is still

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limited, being rarely integrated with machine learning methods.

On top of that, data-driven approaches have demonstrated a significant potential in optimizing organizational decision-making processes and have emphasized the importance of combining unsupervised clustering methods with predictive simulations to reduce subjectivity and increase the accuracy of human resource planning (Ergu & Kou, 2013; Shafie et al., 2024).

The existing approaches to employee performance analysis can be broadly grouped into three categories. First, the traditional statistical and indicator-based methods focus on isolated performance metrics and linear relationships, offering a limited insight into complex organizational structures (Campbell & Wiernik, 2015). Second, the supervised machine learning models aim to predict performance outcomes but typically require predefined target variables and often lack interpretability in managerial contexts. Third, the unsupervised learning techniques, such as clustering and dimensionality reduction, have been used to identify workforce typologies; however, these approaches are predominantly static and do not account for temporal evolution or managerial interventions.

While the simulation-based models have been applied in organizational studies, their integration with unsupervised learning methods remains limited. This gap motivates the development of an integrated framework that combines nonlinear employee segmentation with dynamic performance simulation.

In order to address these limitations, this paper proposes an integrated SOM-kinMod framework for modeling employee performance. Within this methodology, SOM is used for grouping employees based on performance, skills, and development potential, and kinMod is applied for simulating the impact of different management scenarios on collective performance and team cohesion. The integration of the two methods contributes to reducing subjectivity in human resource assessment and provides managers with predictive tools for making informed decisions.

And, although the empirical validation presented in this study refers to human resource management, the SOM-kinMod methodological framework has a general character and can be extended to other fields where structural analysis and dynamic simulation are combined. From this perspective, the main contribution of the proposed method is one related to applied computer science, in which the integration of unsupervised learning algorithms with kinematic models provides a versatile tool for investigating complex organizational systems, characterized by nonlinear relationships and dynamic interactions among the organizational variables. Thus, the human resources field functions in this article only as a validation environment, without limiting the potential for methodological transfer to other areas, such as logistics, network analysis, or risk management (Barbu et al., 2025).

The preliminary results indicate that this approach can support recruitment processes, succession planning, talent retention, and the strategic development of organizations. In addition, the proposed model facilitates a deeper understanding of the interdependencies between individual and collective variables that influence organizational performance.

The remainder of this paper is structured as follows. Section 2 presents the theoretical framework and relevant literature. Section 3 details the research methodology, based on the integration of SOM with kinMod. Further on, Section 4 presents the simulations that were carried out, along with the obtained results, and discusses the limitations of this study. Finally, Section 5 summarizes the main conclusions and highlights the theoretical and practical implications of the findings, while also outlining possible future research directions.

2. Theoretical Framework

In the past two decades, employee performance has become one of the central indicators in assessing organizational competitiveness, being directly correlated with productivity, innovation, and adaptability to market changes (Campbell & Wiernik, 2015; Wright & Ulrich, 2017). Traditionally, human resource assessment has been based on qualitative and subjective methods - interviews, questionnaires, or assessments carried out by hierarchical superiors - which, although providing useful information, are exposed to cognitive biases and fail to capture the complexity of the interactions between employees (Boxall & Purcell, 2016; Ekemeyong Awong &

Zielinska, 2023). Against this background, the integration of data-based methods and artificial intelligence algorithms has opened a new horizon in human resource analysis, allowing for objective and simulation-based insights into organizational performance (Ekemeyong Awong & Zielinska, 2023).

Self-Organizing Maps (SOMs), proposed by Kohonen (2001), are one of the most widespread unsupervised learning methods. SOMs allow the projection of multidimensional data onto a two-dimensional map, maintaining the topological relationships among the data. This mechanism facilitates the identification of clusters, deviances, and hidden relationships between variables, becoming a tool for the analysis of complex data sets (Chen & Kuo, 2019; Yue et al., 2019). In the field of human resources, SOM can be used to segment employees based on factors such as individual performance, the skill level, growth potential, or the level of team integration.

The literature shows that SOM is effective in detecting hidden patterns and visualizing the relationships between employees, but it has major limitations: it only provides a static image and does not allow the simulation of changes that occur over time or under the impact of managerial decisions (Boxall & Purcell, 2016). For this reason, the integration of SOM with other dynamic methods becomes necessary for a complete analysis of organizations.

Kinematic models (kinMods) have been established in fields such as biomechanics and robotics, being used for describing the movement and interactions of the components of a complex system (Ak et al., 2018). Adapted to an organizational context, these models can be used for simulating team dynamics and evaluating the impact of managerial decisions.

An advantage of kinMod lies in its ability to capture developments over time and model hypothetical scenarios (what-if analysis). This feature allows decision-makers to anticipate the consequences of the adopted measures and minimize the risks associated with strategic decisions. However, kinMod in isolation does not provide tools for classifying employees and cannot capture the static structure of organizational data, which limits its applicability if not integrated with machine learning methods.

The combination of SOM and kinMod addresses these limitations and creates a robust analytical framework. SOM provides the initial segmentation of employees into homogeneous groups, based on real and objective data, while kinMod adds a dynamic dimension, simulating possible developments and the impact of managerial decisions (Ban, 2024). Beyond that, their integration contributes to reducing subjectivity and developing analytical and simulation-based models that support decision-making in human resource management.

On this scientific scaffold, the present article aims to develop a methodological framework that combines the advantages of both methods. First, SOM is used for identifying hidden patterns and for building a topological map of employee performance. Subsequently, based on these classifications, kinMod is applied in order to simulate organizational scenarios and to estimate the impact of decisions on collective performance. Thus, the theoretical framework of this paper substantiates a unitary model that not only describes the current state of human resources but also allows the exploration of a possible performance evolution under the influence of managerial decisions.

The integration of these two methods configures a complex analytical framework, the benefits of which are manifested on multiple levels. First, it allows a static visualization of performance and competence structures, facilitating the identification of patterns and employee groupings. Second, it ensures a dynamic dimension by simulating organizational changes, which makes it possible to anticipate the effects of managerial decisions. Third, it contributes to reducing subjective biases and provides decision-makers with solid predictive tools for strategic management. Last but not least, this integration supports the development of an interdisciplinary framework, located at the intersection of computer science, control, and organizational sciences, which strengthens its relevance and applicability in contemporary research.

3. Methodology

Analyzing employee performance requires methodological instruments capable of simultaneously addressing structural heterogeneity and temporal variability within organizations.

From a modeling perspective, this implies combining techniques capable of extracting latent patterns from multidimensional data with mechanisms that allow to explore how these patterns evolve under the managerial influence. To this end, this study adopts a sequential and integrated analytical pipeline that links data preprocessing, nonlinear segmentation, and dynamic simulation within a unified framework.

The implementation of this methodological approach has three stages. First, individual-level employee data is systematically preprocessed through imputation, outlier treatment, normalization, and intra-sectoral standardization in order to obtain a homogeneous and reproducible dataset. Second, Self-Organizing Maps (SOMs) are employed to identify latent workforce structures by projecting high-dimensional employee profiles onto a topologically ordered low-dimensional representation, thereby enabling the construction of homogeneous employee clusters. Third, these static cluster configurations are used as initial conditions for a kinematic model (kinMod), which introduces a temporal dimension by simulating the evolution of the collective performance as a function of skills, satisfaction, absenteeism, and managerial interventions.

The proposed methodology is conceived as a phenomenological and control-inspired modeling framework rather than as a mechanistic representation of individual behavior. Its purpose is not to predict individual performance outcomes, but to support the scenario-based exploration of organizational dynamics while maintaining mathematical transparency, interpretability, and reproducibility.

Let $\boldsymbol{X} = (x_{ij}) \in \mathbb{R}^{Nx4}$ denote the data matrix, where N is the number of employees and x_{ij} represents the value of the characteristic j for employee i, with $j = 1,\ldots,4$.

Each employee belongs to an activity sector denoted by $s(i) \in \{1,\ldots,S\}$.

In this study, each employee i is described by a four-dimensional feature vector:

$$x_i = (P_i, S_i, Sat_i, A_i) \in \mathbb{R}^4 \tag{1}$$

where:

- P_i is the performance score, computed as a composite index combining managerial evaluations with objective indicators such as the achievement of objectives, respecting deadlines, and the quality of deliverables;
- S_i denotes the level of technical and transversal skills, quantified based on the professional experience, training participation, and certifications;
- Sat_i represents organizational satisfaction, measured by using the Likert-scale questionnaire items capturing motivational and psychosocial factors;
- A_i quantifies absenteeism, expressed as the number of absence days over a reference period.

Records with excessive missing information were removed from the dataset. For the remaining data, the missing values were handled independently for each characteristic using median imputation. The imputed value $x_{ij}^{(imp)}$ is defined as:

$$x_{ij}^{(imp)} = \begin{cases} x_{ij}, & \text{if } x_{ij} \text{ is observed}, \\ median(x_{.j}), & otherwise, \end{cases} \tag{2}$$

where median $(x_{.j})$ denotes the median of all the observed values of the characteristic j. This approach was adopted due to the robustness of the median to outliers.

For the satisfaction variable, incomplete questionnaire responses were corrected using subscale-based imputation prior to aggregation. The internal consistency of the satisfaction scale was assessed using Cronbach's alpha coefficient:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k} \sigma_j^2}{\sigma_T^2}\right) \tag{3}$$

where k is the number of items, σ_j^2 denotes the variance of each item, and σ_T^2 the total variance of the aggregate score.

To ensure robustness against extreme values, a winsorization procedure was applied independently for each characteristic. The winsorized value $x_{ij}^{(win)}$ is defined as:

$$x_{ij}^{(win)} = \begin{cases} Q_{0.01}(x_{ij}), & x_{ij}^{(imp)} < Q_{0.01}(x_{.j}), \\ x_{ij}^{(imp)}, Q_{0.01}(x_{.j}) \le x_{ij}^{(imp)} \le Q_{0.99}(x_{.j}), \\ Q_{0.99}(x_{ij}), & x_{ij}^{(imp)} > Q_{0.99}(x_{.j}), \end{cases} \tag{4}$$

where $Q_{0.01}(x_{ij})$ and $Q_{0.99}(x_{ij})$ denote the empirical 1-st and 99-th percentiles of a characteristic.

To reduce inter-sectoral bias, the normalized data was subsequently standardized within each activity sector:

$$z_{ij} = \frac{x_{ij}^{(win)} - \mu_{j,s(i)}}{\sigma_{j,s(i)}} \quad (5)$$

where $\mu_{j,s(i)}$ and $\sigma_{j,s(i)}$ represent the mean and standard deviation of the characteristic *j* computed for all employees belonging to sector *s(i)*.

The standardized values were then rescaled to the unit interval:

$$x_{ij}^{(std)} = \frac{z_{ij} - min(z_j)}{max(z_j) - min(z_j)} \quad (6)$$

The resulting normalized matrix, namely:

$x^{(std)} = (x_{ij}^{(std)})$

constitutes the final dataset used for clustering and dynamic modeling.

To examine the linear dependencies between variables, the Pearson correlation matrix was computed. For each pair of characteristics *(j,k)*, the correlation coefficient was defined as:

$$r_{jk} = \frac{\sum_{i=1}^{N}\left(x_{ij}^{(std)} - \bar{x}_j\right)\left(x_{ik}^{(std)} - \bar{x}_k\right)}{\sqrt{\sum_{i=1}^{N}\left(x_{ij}^{(std)} - \bar{x}_j\right)^2}\sqrt{\sum_{i=1}^{N}\left(x_{ik}^{(std)} - \bar{x}_k\right)^2}} \quad (7)$$

where:

- $\bar{x}_j$ denotes the sample mean of characteristic *j*, computed as the average value for all the employees in the dataset;
- $\bar{x}_k$ denotes the sample mean of characteristic *k*, computed analogously as the average value for all the employees in the dataset.

The preliminary inspection revealed that most correlation coefficients were small in magnitude, with some negative values, indicating that linear relationships alone are insufficient to capture the complex interactions among performance, skills, satisfaction, and absenteeism. This observation motivates the use of nonlinear segmentation techniques.

To identify the latent structures within the workforce, Self-Organizing Maps (SOMs) were applied to the normalized dataset. SOM is an unsupervised learning method that projects high-dimensional data onto a two-dimensional grid while preserving topological relationships.

Each employee vector $x_{ij}^{(std)} \in \mathbb{R}^4$ is mapped onto a SOM consisting of *M* neurons arranged on a regular two-dimensional grid. Each neuron *j* is associated with a prototype (weight) vector $w_j \in \mathbb{R}^4$.

The two-dimensional structure is exclusively related to the topological organization of neurons, while all distance computations are performed in the original four-dimensional feature space.

For each observation, the Best Matching Unit (BMU) *c* is determined as:

$$c = arg\min_j \left\| x_i^{(std)} - w_j \right\| \quad (8)$$

The prototype vectors are updated iteratively according to:

$$w_j(t+1) = w_j(t) + \eta(t) \cdot h_{cj}(t) \cdot \left(x_i^{(std)} - w_j(t)\right) \quad (9)$$

where $\eta(t)$ is the learning rate, and $h_{cj}(t)$ is the neighborhood function, typically Gaussian and decreasing over time and in relation to the distance from the grid.

The SOM training results in a partition of the employee set into *K* clusters: $\{C_1, C_2, ..., C_k\}$.

Each cluster is defined as:

$$C_k = \left\{ i \mid arg\min_j \left\| x_i^{(std)} - w_j \right\| = k \right\} \quad (10)$$

Clustering quality was assessed by using the Davies–Bouldin Index (DBI):

$$DBI = \frac{1}{k}\sum_{i=1}^{K} \max_{j \neq i} \frac{s_i + s_j}{d\left(w_i, w_j\right)} \quad (11)$$

where s_i denotes the average intra-cluster dispersion of cluster *i*, and $d(w_i, w_j)$ is the Euclidean distance between cluster prototypes.

While SOM provides a static segmentation of the workforce, a kinematic model (kinMod) is employed to introduce a temporal dimension. Employee performance is modeled as a dynamic variable influenced by skills, satisfaction, absenteeism, and managerial interventions.

The performance of employee *i* at time *t*, denoted by $P_i(t)$, is expressed by the following first-order differential equation:

$$\frac{dP_i(t)}{dt} = \alpha S_i(t) + \beta Sat_i(t) - \gamma A_i(t) + \delta M(t) - \lambda P_i(t) \quad (12)$$

Here, $\alpha, \beta, \gamma, \delta, \lambda \geq 0$ are constant coefficients and the $M(t)$ factor represents managerial interventions. This equation is interpreted as a first-order phenomenological approximation rather than as a mechanistic model of human behavior.

For empirical implementation purposes, the equation was discretized using the forward Euler method with the time step Δt:

$$P_i(t+\Delta t) = P_i(t) + \Delta t \cdot [\alpha S_i(t) + \beta Sat_i(t) - \gamma A_i(t) + \delta M(t) - \lambda P_i(t)] \quad (13)$$

At the collective level, SOM clusters provide the initial states for dynamic simulations. Let, $\overline{P_k}(t)$, $\overline{S_k}(t)$, $\overline{Sat_k}(t)$ and $\overline{A_k}(t)$ denote the average performance, skills, satisfaction, and absenteeism for cluster C_k. The evolution of the cluster-level performance is modeled as:

$$\frac{d\overline{P_k}(t)}{dt} = \alpha \overline{S_k}(t) + \beta \overline{Sat_k}(t) - \gamma \overline{A_k}(t) + \delta M(t) - \lambda \overline{P_k}(t) \quad (14)$$

This formulation enables the transition from an individual-level analysis to collective dynamics while preserving differentiated responses across organizational segments. Together, SOM and kinMod make up an integrated methodological framework linking static workforce structure with dynamic performance evolution under managerial interventions.

4. Results

The empirical analysis was conducted on a dataset comprising approximately 1,800 employees from Romanian companies operating in four economic sectors: information technology, financial services, retail, and logistics. This dataset reflects a heterogeneous organizational structure, enabling the identification of both common and differentiated patterns of performance and work behavior.

The data was obtained from multiple sources, including internal human resource information systems (HRIS), anonymous employee surveys addressing satisfaction and motivation, and administrative records related to employee attendance. The integration of these data sources enabled a coherent representation of organizational performance, combining individual outcomes, accumulated skills, satisfaction levels, and behavioral stability. To ensure an adequate coverage of organizational variability and to support the exploration of counterfactual scenarios in subsequent simulations, the empirical dataset was supplemented with controlled synthetic augmentations designed to preserve the underlying statistical distributions while increasing modeling flexibility.

In the context of modern organizational environments, the analysis began by investigating the linear relationships between the main indicators of employee performance. The variables considered - individual performance, skill level, job satisfaction, and absenteeism - were analyzed using Pearson correlation coefficients.

The matrix illustrated in Figure 1 indicates that most associations are weak in magnitude, and some of them are negative, suggesting that these factors do not necessarily evolve in the same direction and that a linear correlation alone cannot fully capture their interdependencies. For example, performance is negatively correlated with absenteeism (r = −0.21), while job satisfaction exhibits a similar negative association with absenteeism (r = −0.21). Correlations involving skills are close to zero (r = −0.03 with performance and r = −0.15 with job satisfaction), indicating the absence of a direct linear relationship between the training level and these outcomes.

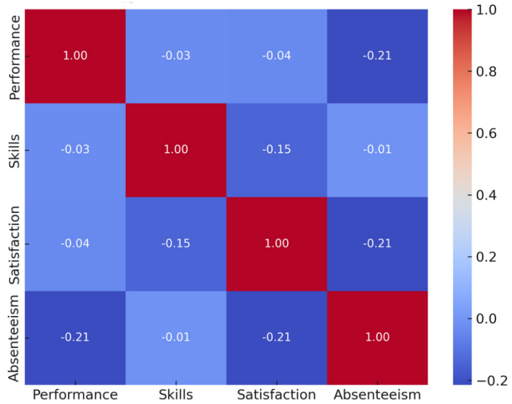

Figure 1. Correlation matrix of KPI variables

In order to gain a more detailed understanding of organizational structure, the data was further analyzed using Self-Organizing Maps (SOMs). The algorithm identified nine distinct employee clusters, each characterized by specific combinations of performance, skills, job satisfaction, and absenteeism. Figure 2 illustrates the resulting groupings in the performance–skills space, while job satisfaction and absenteeism were analyzed at the cluster level. The identified typologies include groups with a high performance but low satisfaction, indicating potential vulnerability with regard to turnover, as well as clusters characterized by strong skills and an elevated absenteeism, suggesting motivational or organizational climate issues. Other clusters exhibit low values across all four dimensions, highlighting areas where mentoring and development interventions may be required. Intermediate typologies were also observed, representing potential strategic resources if supported through appropriate retention and training policies.

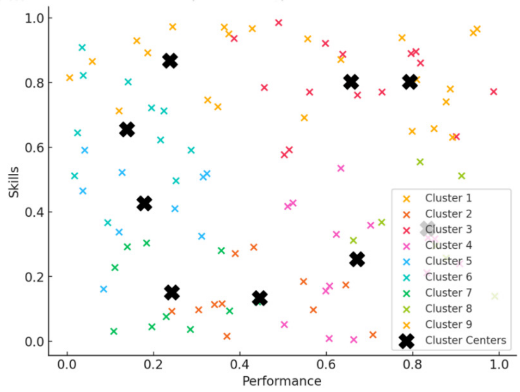

Figure 2. Employee clustering based on performance, skills, and job satisfaction

Following cluster identification, the results were integrated into a kinematic model (kinMod) in order to simulate the dynamics of collective performance. The first scenario, illustrated in Figure 3, represents a situation in which the managerial responses are delayed or implemented without a coherent long-term strategy. The resulting collective performance trajectory exhibits a downward trend, characterized by gradual degradation over time. This behavior indicates that, in the absence of sustained and coordinated interventions, the imbalances related to skills, job satisfaction, and absenteeism tend to increase, leading to efficiency losses that are difficult to reverse.

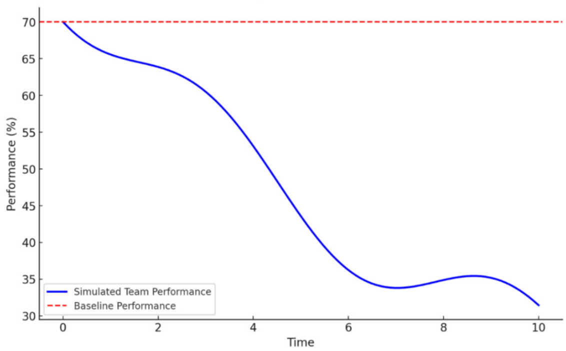

Figure 3. The kinMod simulation: the impact of delayed managerial interventions

In a second scenario, the coefficients estimated through regression models were incorporated into the kinMod equations to reflect the interactions between the KPI variables. As shown in Figure 4, coordinated managerial actions can lead to short-term performance improvements. However, the resulting dynamics is neither linear nor stable, with the performance oscillating around a mean level and alternating between phases of increase and decrease. These oscillations suggest organizational adjustment processes following managerial interventions, indicating that the performance outcomes depend not only on the number of decisions implemented but also on their coordination and consistency over time.

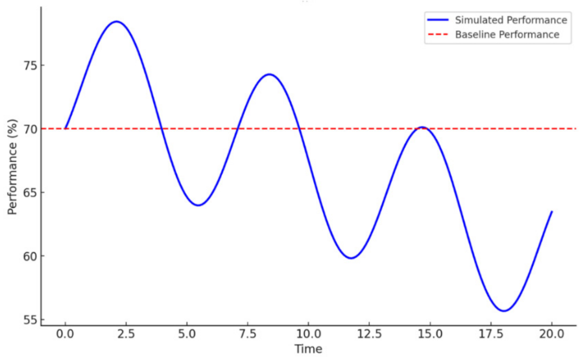

Figure 4. Integrated kinMod dynamics with regression-based parameters

The final scenario simultaneously integrated all the variables considered in the analysis - skills, job satisfaction, absenteeism, and managerial decisions - to approximate the organizational climate more closely. As illustrated in Figure 5, the resulting dynamics is oscillatory, with alternating phases of growth and decline around an average performance level. These irregular fluctuations reflect the sensitivity of collective performance to interacting factors and indicate that organizational outcomes cannot be reliably assessed immediately following the implementation of a management policy, but require continuous monitoring over time.

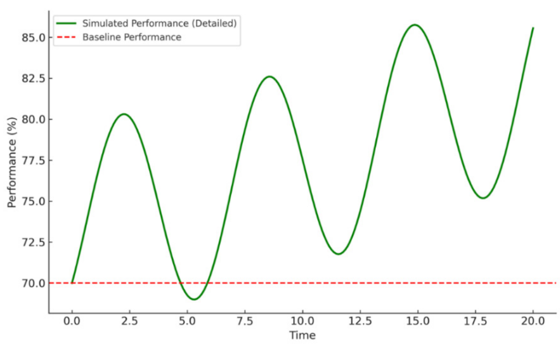

Figure 5. The kinMod dynamics simulation with all the KPI variables integrated

Together, the three analytical levels - correlation analysis, segmentation, and dynamic modeling -provide a comprehensive perspective on organizational behavior. The correlation matrix highlights the limitations of linear analysis, the SOM-based segmentation reveals recurring employee typologies with practical relevance, and the kinMod simulations illustrate how the collective performance evolves under different managerial scenarios. By integrating these methods, the proposed framework complements static diagnosis with a dynamic, scenario-based analysis.

Table 1 compares the performance of the proposed SOM–kinMod framework with that of the classical clustering (K-means) and standard predictive models (Random Forest and SVM). The Davies-Bouldin Index indicates an improved cluster cohesion for SOM, while the lower RMSE and MAE values obtained by the SOM–kinMod framework suggest an improved empirical accuracy for the analyzed dataset. These results support the added value of integrating SOM with kinematic modeling.

The interpretation of these results should be considered in the light of several contextual and methodological constraints. The analyzed dataset originated exclusively from Romanian organizations across four economic sectors, which may limit the generalizability of the findings to other cultural or industrial environments. Moreover, the selected variables - individual performance, skills, job satisfaction, and absenteeism - do not exhaustively represent the complexity of organizational processes, as factors such as leadership style, organizational culture, or external conditions were not explicitly modeled. From a methodological perspective, SOM-based segmentation is sensitive to initialization parameters, while kinMod relies on a simplified mathematical representation that may not capture all the subtle interactions which are present in real organizational systems.

5. Conclusions

The integration of self-organizing maps with kinematic models generated an analytical framework capable of jointly addressing latent organizational structures and their evolutionary dynamics. The results confirm the added value of combining these methods by extending human resources assessment beyond the static evaluation toward a scenario-oriented and decision-support tool.

The mapping obtained through SOM revealed the internal diversity of organizations and highlighted latent patterns linking performance, satisfaction, and absenteeism. The identification of these typologies facilitates the formulation of differentiated management policies oriented toward strengthening the vulnerable areas and capitalizing on the existing competencies.

Through kinMod, the static analysis was complemented with a dynamic modeling dimension, enabling the simulation of organizational responses to managerial decisions. The oscillations and imbalances observed in the simulations indicate that the collective performance does not evolve linearly but depends on interacting organizational factors that are difficult to capture using conventional static methods.

The contribution of this paper lies in the direct articulation of these analytical levels within a unitary framework, enabling both the identification of organizational typologies and the exploration of their possible evolutionary trajectories. Through this integration, the fragmentary nature of the existing studies is addressed, and an interdisciplinary methodology is proposed that supports the systematic exploration of complex organizational dynamics. While this framework does not aim to fully formalize the emergent organizational behavior, it provides a structured setting for analyzing the

Table 1. Comparison of the performance of the SOM–kinMod method with that of standard models

Model	DBI (clustering)	Silhouette	RMSE	MAE
K-means	1.42	0.35	-	-
SOM	0.91	0.54	-	-
Random Forest	-	-	0.127	0.093
SVM	-	-	0.139	0.101
SOM–kinMod	-	-	0.111	0.082

adjustment patterns arising from the interaction of multiple factors.

The integration of the two methods brings about several theoretical and practical contributions. First, it reduces the dependence on traditional subjective assessments by providing a objective, data-driven framework for organizational analysis.

Second, it combines static analysis (diagnosis) with dynamic simulation, transforming the research from a purely descriptive exercise into a prospective and exploratory modeling approach. Third, it establishes an interdisciplinary framework at the intersection of computer science, control-inspired modeling, and organizational sciences, extending the applicability of SOM and kinMod beyond their traditional domains.

In a broader perspective, the utility of the SOM–kinMod framework extends beyond human resources, as this methodology can be applied to other organizational or socio-technical contexts in which the interacting components and dynamic adjustment processes influence the collective performance. Through its generic structure, this framework also constitutes an applied computer science contribution, providing a transferable tool for analyzing and simulating various processes in diverse organizational systems.

Building on these considerations, several directions for further development emerge. Extending the application of the SOM–kinMod framework to international samples and additional industries would allow the assessment of its robustness across diverse organizational contexts. Furthermore, the integration of advanced modeling approaches, such as deep learning architectures, agent-based simulations, or Bayesian frameworks, may enhance the representation of complex organizational dynamics. To that, the use of longitudinal datasets tracking employee trajectories over time could further enrich the dynamic perspective introduced in this study.

In parallel, the development of software applications or interactive dashboards implementing the SOM–kinMod framework could facilitate the transfer of analytical results into managerial practice. While the initial benchmarking against the K-means, Random Forest, and SVM models indicates a favorable empirical performance, further comparative evaluations involving deep learning and agent-based models would strengthen the methodological positioning of the framework. Such developments could support the evolution of the proposed approach toward an operational decision-support tool for strategic human resource management.

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