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Evaluation of the Digital Transformation's Impact on Organizational Culture and Employees' Motivation

Abstract. *This study analyses the impact of the digital transformation on organizational culture and Romanian employees' motivation, reducing the Eastern European gap regarding the machine learning (ML) predictive analysis of the cultural dynamics, supported by a powerful interactive data visualization proprietary tool.*
The data was collected via questionnaires from 1,004 employees. A hybrid machine learning approach was employed, combining KNN as a supervised learning algorithm in three dimensions - organizational culture, digital transformation intensity, and internal agility - with traditional binary classification and Support Vector Machines (SVM). SVR predicted cultural evolution influenced by digital pressure and adaptability, enhancing understanding of digital transformation impacts. The analysis identifies distinct cultural clusters, differentiating rigid hierarchical structures from agile, experimental profiles. Support Vector Machine (SVM) results highlight a strong link between digital maturity, agility, and adaptive cultures, effectively categorizing organizational types. Support Vector Regression (SVR) indicates a shift toward flexible cultures with less resistance to change. Positive correlations exist between digital maturity and motivation, although perceptions of AI enhancement and reduced change resistance influence these relationships, reflecting ongoing cultural transformation.
The success of the digital transformation has an important dependence on cultural adaptability, and not just on the technology itself. Managers are recommended to use scalable machine learning tools to detect early on the cultural barriers and establish targeted interventions, in the Romanian context/East European one. Descriptive-predictive integration focuses on the human factor.

Keywords: *organizational culture, digital transformation, Machine Learning, K-Nearest Neighbours, Support Vector Machines, Support Vector Regression, employee motivation.*

JEL Classification: M14, M15, C45, O33.

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1. Introduction

As technology progresses, rapid digital transformation significantly impacts internal company operations. Instead of viewing traditional practices as fixed, there is a growing emphasis on shared values and common rules. This shift highlights the increasing importance of an adaptable organizational culture in navigating technological advancements and maintaining competitiveness in a dynamic environment. The organization's capacity to navigate major transitions heavily depends on the implicit atmosphere behind digital interfaces. Currently, the focus is on how collective mindsets are adjusting to the rise of automation and extensive data analysis, which significantly influence organizational resilience and adaptability in a rapidly evolving technological landscape. Lacking profound adjustments in the way collaboration is handled is what makes even the most sophisticated tools return poor results. Nonetheless, when internal regulations support experimenting and accepting that there is room for error, then switching to new models becomes a more tangible reality. This type of environment does not occur spontaneously – it is built gradually through daily decisions taken by leaders. Thereby, the cultural evolution becomes a constituent part of the strategic survival in unstable conditions.

Transformation through digitalization is deeply affecting the way in which people are working together, clearly highlighting the fact that a company's evolution is not based solely on new equipment. A report released by McKinsey in 2018 indicates the fact that (≈75%) of the digital projects come to a standstill, and the main reason is the difficulties raised by human adaptation, and to a much lesser extent, the technical problems. More studies are supporting the idea: the Gartner predictions for 2025 suggest that only 48% of such initiatives reach the intended target, and 2021 BCG data is placing global efficiency at 35% of the initial target, with most of the failures being linked to the internal environment and relationships' structure. The numbers speak for themselves – when the regulation is too strict, led by top-down authority, the change process stands still, employees' desire to actively participate drops significantly, and the company's capacity to create a quick reaction falls sharply. Open environments fostering daily dialogue and continuous personal growth lead to increased employee engagement, higher retention rates, and surpassing expected performance levels. As external pressures grow, organizations must develop internal agility to adapt effectively, ensuring sustained success and resilience in a competitive landscape. Although old cultural evaluation techniques of companies – such as structured questions or deep discussions – sometimes unravel useful aspects, these are often confronted with personal interpretation; they cannot easily grow in dimension and are missing the fast movements of the collective behaviour (Hartnell et al., 2011; O'Reilly et al., 2014). Moreover, the current automated learning leaps – known as machine learning – offer methods that can process information clearly, rigorously, anticipating multiple angle evolutions. In this context, solutions such as K-Nearest Neighbours (KNN), used for primary grouping of data, the Support Vector Machines (SVM) applied in stable differentiation and the regression based on the same principle (SVR), are helping to detect models specific to the organizational environment, by exploring connections between the institutional attitudes, level of digital integration and response to the continuous transformation (Li et al., 2021; Schachner et al., 2024). The main question of the study focuses on the digital transformation effects on the organizational culture and on the employees' desire to work, notably in Eastern European areas, such as Romania, where digital changes face resistance mainly due to the traditional structures and rigid systems (Văduva et al., 2025; Moga et al., 2024). At the same time, current sources indicate a great distance between what was studied until present - many of them being at an observational or narrative level only – and the need for predictive models based on ML techniques to anticipate the cultural transformation generated by the digital factor (Reisberger et al., 2025; Busco et al., 2023). Given that very few authors have had practical testing on complex methods that can put together diverse data with the help of performant computer tools, the application dimension in organizational leadership remains poorly explored. This study aims to explore the above-mentioned issue in four distinct directions. First, we are looking at grouping the organizational culture types by using the KNN method, together with dynamic graphic representations for complex data that combine culture, digital transformation, and flexibility. Then the companies are analysed by the degree of deeply ingrained in traditional culture versus culture open to digital changes, a separation made with the SVM model, chosen for its accuracy. Further on, the expected evolution of the organizational culture is predicted based on the simultaneous pressure of the digital transformation and the adapting capacity, possible through an SVR-based system. At the end, the effects on the employees' motivation are measured, starting from practical data gathered under local Romanian conditions.

2. Literature Review and Approaches

The culture of a company includes what employees tacitly accept: the way they perceive the world, how they act daily. The common grounds – values, convictions, or habits – modulate the individual decisions and reactions to change, according to Schein (2010). For that matter, the traditional tools have developed practical methods to measure this complexity from different angles. The model proposed by Hofstede (1991) introduces dimensions such as preference for collective versus individual, hierarchy tolerance, fear of the unknown, differences between masculine and feminine, and planning for the future. Each one of these shows how different the ways of working can be between organized groups. On a different note, Cameron and Quinn (2011) introduced a framework based on internal tensions: clan culture, where the relationships are warm and tend to build loyalty; adhocracy, centred on experimenting and speed of answer; markets, dominating through visible performance and rigid order.

The Denison and Mishra study from 1995 connects the way of working in an organization with its internal atmosphere, starting from four key elements: the degree of involvement of the employees, the coherence of the internal regulation, the capacity of adaptation to external changes, and the precision of the declared objectives. Over the years, this structure has proven useful in various practical situations, being confirmed through a complex series of analyses (Hartnell et al., 2011). Nonetheless, some specialists notice that traditional approaches often ignore the evolution in time, underestimate the impact of rapid transformations brought by society – e.g., the technical advancements – or easily overlook the relationships between people and digital tools (O'Reilly et al., 2014). In the Central and Eastern Europe, including in Romania, the GLOBE project data (House et al., 2004; updated in 2020) underlines the presence of a centralized managerial style and an increased resistance to uncertainty, consequences of the post-communist context, even though there are clear indications of mutation towards approaches based more on results and experimentation (Bakacsi et al., 2002; Văduva et al., 2025).

2.1 The impact of the digital transformation and intelligent technologies on the organizational culture

Recent studies confirm the essential role of human behavior when it comes to general technical success. Considering the technological evolution in the Eastern European area, Romania included the leap towards digital transformation is lengthier due to the old structures and rigid systems. Therewith, the government planning and EU initiatives are bringing a visible stimulus to the whole process. The institutions that are rapidly adapting show a greater capacity to react to the sudden changes brought by innovation. Even so, few studies follow the long-term evolution of the employee's desire to work in the private or public sector when they are affected by the digital transformation.

2.2 Implementing machine learning in the analysis and quantification of the organizational culture

Over the past years, the changes in the machine learning sector have opened the way towards an approach based less and less on subjective opinions. Data analysis has now become extended and measurable, providing clear perspectives regarding the culture of an organization. These tools unravel regularities often ignored by old techniques – as in Li et al.'s research, published in 2021. A concrete example comes from using linguistic vectors generated on financial texts: annual reports or investor meetings can showcase the real level of some of the internal values. Therefore, traits such as creativity, correctness, or employee care are transformed into indicators measured without direct human intervention.

Grouping techniques analyse the connection between the organizational climate and the professional results when applied to the work environment (He et al., 2023). Nonetheless, recent studies draw attention to the fact that using them can generate profound issues: decisions influenced by biases of automated systems, operational opacity, or negative effects on certain employee categories (Murire, 2024).

2.3 Relevant studies and literature in the Romanian and East-European context

Romanian research indicates important changes in the organizational culture imposed by the digital era. By analysing the impact of artificial intelligence, Pelau (2024) has shown how adaptability sustained by permanent learning is no longer an option, but a vital necessity for companies. Instead of limiting itself to technology, another study – Stăneiu et al. (2024) – is following the way in which leaders perceive and integrate AI in local IT&C, focusing on employees' development. The transformation of internal behaviors is seen as a part of a large mutation where mental practice meets the technical strategy. Other local contributions underline regional particularities: the Romanian management is combining traditional hierarchical elements with Western influences (Vaduva et al., 2024), and employees' performance in multinational companies is closely related to cultures oriented towards relationships and cohesion (Stratone, M.-E. et al., 2025). In a larger Eastern European context, the digital transition is influenced by the post socialist institutional heritage, which generates change resistance but also opportunities for technological leaps (Moga et al., 2024; Pavel et al., 2020).

2.4 Literature gaps and proposed contribution

Though the literature has grown significantly when it comes to quantifying culture through machine learning and in the analysis of the digital impact, important gaps are still present. Most of the studies remain descriptive or limit themselves to static classifications, lacking the longitudinal predictive approaches that can estimate the future evolution of the culture under the combined influence of both digital transformation and flexibility to change (Reisberger et al., 2025; Busco et al., 2023). Notably, in the Eastern European and Romanian contexts, the empirical analysis that integrates SVM and SVR for prediction is rare, and the cross-analysis with the employees' motivation remains under-explored (Ciuculescu et al., 2024). Moreover, the ethical risks and the biases of algorithms when it comes to evaluating culture are insufficiently addressed (Shah, 2025). This study contributes to reducing these gaps by proposing an integrated approach that combines interactive visualization and KNN clustering to identify cultural typologies, SVM robust classification of the organizations depending on the influence factors' prevalence (traditional culture vs. adaptive culture), and estimation of future evolution through SVR. Applied to multidimensional empirical data collected in the Romanian area, the methodology provides a quantitative perspective, scalable and predictive, useful for both research and management practice in the accelerated digital transformation era.

3. Data acquisition

This section presents the way in which information has been gathered and organized regarding how digital changes affect the internal culture in companies and people's desire to work. Instead of making use of personal opinions, the research has combined them with clear measurements to avoid frequently encountered errors when all data comes from the same source (Podsakoff et al., 2003). The data collection aimed at clarity, the possibility that others can repeat the study, and adherence to ethical standards, according to the journals' requirements, famous in management or informatics systems (Hair et al., 2019). This information has created the basis for the algorithms' functionality: some by grouping similar cases through K-Nearest Neighbors (KNN), others by separating different types with support vector machines (SVM), and some by estimating future values through an adapted form of regression (SVR).

3.1 Population sampling

The target population was made up of adult employees (≥ 25 years old) with a minimum of two years of professional experience in public or private sector organizations of Romania, who interact regularly (at least weekly) with advanced digital technologies (artificial intelligence tools, Large Language Models – LLM, big data analytics, cloud computing) in activities of data processing, automation or decisional support.

To balance the statistical strictness and the practical feasibility, we've applied a hybrid sampling strategy (Saunders et al., 2019):

- Stratified probabilistic component (n=602 respondents), extracted from official sources (commercial databases and public administrative registers, in compliance with GDPR). The stratification aimed to approximate proportions: public sector 58% / private 42%; Bucharest 40% / other regions 60%; managerial positions 30% / operational 70%.
- Non-probability sampling component (convenience + snowball, n = 402), created through online professional networks (LinkedIn, Facebook professional groups) to increase the diversity and cover less accessible segments.

Data was collected between November 2025 and January 2026, generating initially 1,927 samples. Quality controls (through automated R scripts) have eliminated the incomplete samples (< 85% completed), the uniform answering patterns (straight-lining, standard deviation < 0.5), and logical inconsistencies, resulting in a final valid sampling of 1,004 participants (adjusted answering rate of ≈ 52%). The eligibility was confirmed through screening questions, supported in 35% of cases by voluntary objective data (LLM usage logs). A longitudinal sub-sample (n = 250), with a retention rate of 92%, was used to allow preliminary evaluations of the temporal dynamics. Table 1 presents the descriptive statistics of the sampled demographics.

Table 1. Demographic characteristics of the sample (N = 1,004)

Variable	Category	Frequency	Percentage (%)
Gender	Male	481	48
	Female	522	52
	Other / Rather not choose	1	<1
Age group	25–34 years old	201	20
	35–50 years old	683	68
	51+ years old	120	12
Sector	Public	582	58
	Private	422	42
Area	Bucharest	402	40
	Other regions	602	60
Employee position	Management	301	30
	Operational	703	70
Experience in the company	2–5 years	452	45
	6–10 years	351	35
	11+ years	201	20
LLM exposure (average, standard deviation)	Scale: 1 (low) – 5 (high)	3.2 (1.1)	–

Source: Author data processed.

Note: LLM exposure was auto-reported and correlated with objective logs where available ($r=0.72$, $p < 0.001$).

This composition improves the generalization in the Romanian context, although some limitations linked to the selection bias persist in the non-probabilistic component and the respondents' overweighting on advanced digital skills. These aspects have been reduced by applying adjustments according to the national workforce statistics (National Institute of Statistics, 2023).

3.2 Measurement tools

The key constructs have been evaluated on a 5-point Likert scale, adapted from internationally validated tools and submitted to double-reversed translation (Brislin, 1970). The pilot test conducted on 50 participants confirmed the clarity and reliability (Cronbach $\alpha > 0.80$). The main constructs, inspired by established models (OCAI – Cameron & Quinn, 2011; Denison & Mishra, 1995), include:

- Change resistance (adapted from Oreg, 2003; 6 items);
- Individual digital skills (adapted from van Laar et al., 2017; 5 items);
- Organizational agility (adapted Denison & Mishra, 1995; 4 items);
- Motivation oriented towards public interest/services (adapted from Perry, 1996; 6 items);
- Perception regarding the digital work environment (adapted from Venkatesh et al., 2003; 5 items);
- Balancing of the AI enhancement (original scale; 4 items – mediator);
- LLM exposure (continuous mediator; 3 items + objective logs)

Table 2. Main items used for key constructs' measurement

Construct	Used items
Change resistance	1) I'd rather use the current habits and avoid changes. 2) When a change of plans is mentioned, I feel stressed. 3) Changes seem like a useless hassle in the short term. 4) It is hard for me to change my mind once I have an opinion on the subject. 5) I believe most of the changes are negative. 6) I oppose changes that are disturbing my stability.
Individual digital skills	1) I manage the digital information efficiently, and I also provide a critical evaluation. 2) I communicate efficiently using digital tools (email, collaborative platforms). 3) I work online with my colleagues with no issues or difficulties. 4) I generate creative ideas by using digital technologies. 5) I solve complex technical issues by using digital resources.
Organizational agility	1) Our organization creates and implements changes rapidly. 2) We pay close attention to the clients' needs and the market. 3) We learn continuously from mistakes and experiences. 4) We adapt easily to new requirements coming from the external environment.
Motivation oriented towards public interest/services	1) Public policy is of interest, and I'm also paying attention to the decision-making process. 2) It is important to contribute to the public well-being through my work. 3) I feel compassionate towards those in difficulty. 4) I'm willing to make some personal sacrifices for the public well-being. 5) I'm motivated to promote transparent and fair policies. 6) I have a strong sense of civic responsibility.
Perception regarding the digital work environment	1) I am provided with the necessary technical resources (hardware, software) to complete my tasks. 2) I am provided with the necessary support when facing digital issues. 3) The digital infrastructure (internet connection, cloud) is reliable. 4) There are training and guides for the digital tools in use. 5) The digital work environment is facilitating my daily productivity.
Balancing of the AI enhancement	1) The AI usage is improving the performance without replacing me. 2) AI is helping me make informed decisions without being a burden. 3) I feel there is a good balance between the human contribution and AI in my tasks. 4) AI takes care of the repetitive tasks, allowing me to be more creative.
LLM Exposure	1) How often do you make use of the large linguistic machines (ex. ChatGPT, Grok, etc.) in your daily activities? 2) How often do you integrate LLMs into your job's workflow? 3) To what degree are LLMs part of your usual tools?

Source: The authors' own creation.

Validation has been obtained through confirmatory factor analysis (CFA) in PLS-SEM (R semPLS package, bootstrapping 5,000 repetitions). Table 2 synthesizes the reliability and validation metrics.

Table 3. Reliability and validity of the constructs

Construct	Cronbach α	Composite reliability (CR)	Average variance extracted (AVE)	HTMT (maximum report)
Change resistance	0.92	0.93	0.78	0.82
Digital skills	0.89	0.91	0.72	0.79
Organizational agility	0.87	0.89	0.70	0.84
Public motivation	0.85	0.88	0.68	0.81
Digital work environment	0.82	0.86	0.65	0.83
AI enhancement balance	0.88	0.92	0.74	-
LLM Exposure	0.87	0.91	0.71	0.78

Source: The authors' own creation.

Note: All values fulfil the recommended criteria ($\alpha > 0.80$; CR > 0.85; AVE > 0.65; HTMT < 0.85; Hair et al., 2019). The continuous variables have been mean-centered to minimize the multicollinearity (VIF < 3.0).

3.3 Data collection procedure

The data has been collected via online platforms, Google Forms/Microsoft Forms. The invites have been sent via email (probabilistic sampling) or shared links. The consent provided electronically has included the purpose of the study, the voluntary participation, anonymity, and withdrawal rights. For the objective data, a separate consent has been requested. The average time of completion was around 14 minutes. Those selected for the long term have received reminders with summaries to keep them motivated.

3.4 Data processing and ethical considerations

Raw data was processed in R. The missing values (<5%) were filled through multiple imputation using the MICE package (van Buuren & Groothuis-Oudshoorn, 2011; 5 iterations, predictive mean matching). The outliers have been analysed through Mahalanobis distance ($p < 0.001$ threshold). The normality has been checked (Shapiro-Wilk test) with logarithmic transformations where necessary.

The study has fully respected the General Data Protection Regulation (GDPR): data minimization, pseudonymization, and secure storage on EU servers. The participants were debriefed and received contact data.

The main limitations include the auto-reporting bias (mitigated through triangulation), non-response bias (compared between early/late respondents), and generalizability limited to the Romanian context (digital adaptation is lengthier in the public sector; Eurostat, 2023). The analysis code and anonymized data are available upon request. The processed data (constructs; standardized scores) have been used as input for multidimensional projections and KNN clustering (chapter 4), SVM classification (chapter 5), and SVR estimation of the cultural evolution (chapter 6). The model, based on structural equation modelling (SEM), used the maximum likelihood estimation technique and was run in IBM SPSS AMOS. To begin the analysis, the normal distribution of the data was first checked. Table 1 presents the assessment of normality, and it can be seen that both skewness and kurtosis describe relatively good normality values for each indicator measured. The multivariate kurtosis value of 38.87 is well below the mean limit of 78.70 recommended by experts (Cain et al., 2017).

4. Methods

4.1 Analytical strategy and machine-learning pipeline

This section describes the analytical strategy and the machine-learning methodology applied to the validated constructs presented in Section 3, keeping the methodological description separate from the empirical findings reported in Section 5. The analysis follows a sequential and integrative pipeline. First, the standardized construct scores were projected into a three-dimensional space defined by organizational culture, digital-transformation intensity, and internal agility. To identify the natural cultural typologies and generate the visualization presented in Figure 3, the observations were grouped using the K-Means clustering algorithm. This unsupervised learning technique partitions the data into homogeneous clusters by minimizing the within-cluster variance and maximizing the separation between groups (Subsection 4.2). The resulting structure was then submitted to a Support Vector Machine (SVM) classifier that separates traditional from adaptive cultural profiles according to the predominance of the influence factors (Subsection 4.3); its mathematical foundation, the base model expressed as a primal and dual quadratic-optimization problem, is detailed in Subsection 4.4. Finally, the expected cultural evolution under the joint pressure of digital transformation and adaptability was estimated through Support Vector Regression (SVR), which extends the same margin-based principle to the continuous case (Subsection 4.5).

All computations were carried out in R, using the e1071 and kernlab packages for the SVM and SVR estimators, which rely on the LIBSVM routines (Chang & Lin, 2011), together with the authors' proprietary interactive tool for the three-dimensional visualization of the cultural space. A radial-basis-function (Gaussian) kernel was adopted for the non-linear separations, while the regularization cost C, the kernel width, and the SVR insensitivity margin were tuned through a grid search with five-fold cross-validation. Continuous predictors were mean-centred and standardized to limit multicollinearity (VIF < 3.0), and the stability of the estimators was assessed against the reliability and validity metrics reported in Section 3. The schematic diagrams used to illustrate the geometry of the classifier and of the regression tube (Figures 3 and 4) are conceptual and support the methodological description, whereas the empirical outputs derived from the collected data are presented in Section 5.

4.2 Identifying organizational culture models by using machine learning algorithms

Organizational culture includes a great number of values, beliefs, rules, and habits promoted by the members of the organization.

Although it is hard to have it measured, it can be easily recognized through the way in which employees of a company communicate with each other, and how they work towards the accomplishment of their mission.

Thus, beyond written or tacit rules, the organizational culture seems to have some physical manifestations, depending on people's behavior and the support provided by the company to ensure ways of working that are based on unity, efficiency, and a high level of cohesion and adherence to the values that define it.

The influence factors are multiple, but under the circumstances of growing digital transformation, the employee's openness to change and adaptation to the new strategies represent the key element.

We tried in the following paragraphs to identify a few categories of organizational culture, based on their constitutive elements and the influencing factors. Our work will be guided to a great extent by the data visualization process.

4.3 Using the Support Vector Machine algorithm for classification in the organizational culture field

We are aiming to separate into two classes the studied and marked points in the tridimensional space (organizational culture, digital transformation, change flexibility) depending on the predominance of the influence factors.

Most machine learning methods rely on identifying patterns by separating elements of groups of points using hyperplanes, based on their multidimensional coordinates (features); thus, the separation is linear and quite restrictive. The hyperplane equation is then used as a predictor to identify the class to which future observations belong. One of the first attempts to overcome the linear restriction was represented by the decision trees, which do not solve the problem of the local minimum trap in search of the global optimum. The solution appeared in the '90s and is based on the introduction of quadratic optimization elements. Support Vector Machines (SVM) implies the identification of the shapes not through a hyperplane, but with a band (margin) as large as possible, delimited by two parallel hyperplanes to the separation one (fig. 1). Although in a certain area the points of the two classes (categories, shapes) are mixed, the human eye notices where the points are rare and therefore the possibility of a separation region exists; the algorithm is acting similarly and will place there a separation band, orienting it so it can be as wider as possible.

Maximizing the separation band is equivalent to enhancing the classification's resistance to future disruptions and thus to the possibility of using it for a longer period of time, without losing its relevance or needing a recalculation. Practically, this can be translated to a greater flexibility of the classifier in the sense of its usage to correctly classify some observations that are quite different from the training set observations.

Maximizing the separation band's width presented as a convex optimization problem, completed with slack variables and acceptance of some points placed right in the interior of the margin, without attributing them to a class or another; this way, we can establish a compromise between the band's width and accepting eventual classification errors. The features, to which there is a one-point coordinate, correspond in the n-dimensional space and contribute differently to determining a separation hyperplane. Some features leave a stronger mark on the identified shapes; others are less important when it comes to delimiting categories.

This turns into the possibility that, once a separation plan has been identified, it may not be the only one possible, and the identified plans can also generate other ones through the coordinates' inclination of the space features for which the separation flexibility is greater. Out of the multitude of existing hyperplanes, the optimization chooses the direction for which we can build a band delimited by two parallel hyperplanes, between which the distance is maximum. At the *n*-dimensional points' level, we can see a similar phenomenon: some points are closer to the separation band, others are further away, and with a smaller risk of being wrongly classified. Points found closest to the separation band represent **the support on which we based the hyperplane coordinates' calculation** that crosses the middle of the separation band; thus, the idea of calling the method SVM. Therefore, the support vectors are the ones placed near the decision surface, hardest to classify, and affected by the **soft margin** phenomenon, meaning the widening of the band through acknowledgement of some **unclassified** points (inside the band) or **wrongly classified (misclassification,** which means they were arranged in another class than what the separation tag indicated). Classic regression and classic neuronal networks take into account the influence of all points to determine the separation plan equations; **SVM chooses among the points only the most important ones, the critical ones, that if eliminated or modified, would produce major changes in the separation hyperplane equation.** Though it's a matter of separation margin, we often talk about a **separation hyperplane,** meaning the one in the middle of the margin, as the band will be delimited by two parallel hyperplanes to this one, at an equal distance on each side of the separation hyperplane; the three hyperplanes being parallel, their equations differ only by the intercept usually noted as **b – bias** or displacement.

4.4 Base model (Primal Simplex Algorithm)

If $w^T x + b = 0$ is the equation of the searched plane, which will divide the set into two classes, one for which $w^T x + b < 0$ and another one for $w^T x + b > 0$**.**

In practice, these classes are noted as $y_1 = -1$, and $y_2 = +1$, so the classifier used afterwards for the class prediction for a given observation can be written as:

$$f(x) = sign(w^T x + b)$$

The solution's base is a set of training points whose class is known; **the distance from a given *x* point to the hyperplane** is expressed by:

$$d = \frac{w^T x + b}{||w||}$$

Assuming the hyperplane is at the half $\boldsymbol{\rho}$ distance between the two planes that delimit the two classes, then the points of the two classes will fulfil the conditions:

$\mathbf{w}^T\mathbf{x}_i + \mathbf{b} \leq -\boldsymbol{\rho}/2$ if $y_i = -1$ (also called the negative class), respectively, $\mathbf{w}^T\mathbf{x}_i + b \geq \boldsymbol{\rho}/2$ for class $y_i = 1$ (also called the positive class), which equates with the following: $y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq \boldsymbol{\rho}/2$. It can be simplified as $\boldsymbol{\rho}/2$, which would lead to the distance being expressed from each support vector to the separation hyperplane under a simplified form:

$$d = \frac{y_s(w^T x_s + b)}{||w||} = \frac{1}{||w||}$$

Given that the separation band dimension is the double of the distance, the problem returns to the **maximization**:

$$\rho = 2\,d = \frac{2}{||w||}$$

For all pairs *(xi, yi), i =1..n,* fulfilling the restriction: $yi(w^T xi + b) \geq 1$, which comes back to minimizing the denominator, possibly even squared (the two functions reaching the minimum in the same point) to eliminate the root:

$$\frac{1}{2}\|w\|^2$$

Most often, the points are well mixed, and there is no separation plan, even less a separation band; in these cases, we are willing to accept, for the rare points area, the wrong classifications within reasonable limits.

When formulating the mathematical model, this is equivalent to adding compensation variables (slack variables) $\xi_i \geq 0$ by associating them also with a *C* penalty cost. The penalty value is the same for all points that are wrongly classified, regardless of how much they break the placement rule.

Thus, the final form of the model becomes:

$$\frac{1}{2}\|w\|^2 + C\sum_{i}^{n}\xi_i$$

under restrictions: $y_i(w^T x + b) \geq 1 - \xi_i,\ \xi_i \geq 0\ i = 1, \dots, n$

The problem brought to this formula is a squared optimization under some linear restrictions, which is solved with Lagrange multipliers; more precisely, by formulating the dual problem, we will search for the α_i multipliers: $\boldsymbol{\max L(\alpha) = \Sigma}\ \alpha_i - \frac{1}{2}\Sigma\Sigma\ \alpha_i\ \alpha_j\ \boldsymbol{y_i y_j x_i^T x_j}$ under restrictions:

$\Sigma\ \alpha_i y_i = 0$

$\alpha_i \geq 0$ for any i

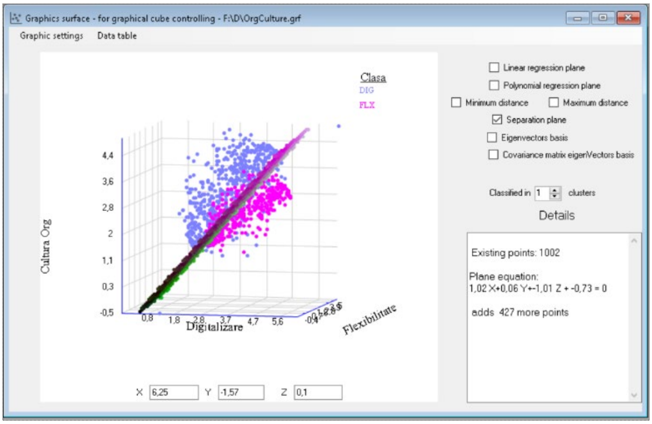

Figure 1. SVM hyperplane for separation into two classes based on the factors' influence
Source: Generated by the authors' own software.

4.5 Estimating the organizational culture evolution through Support Vector Regression

The classic linear regression model supposes that starting from a set of observed points, we can determine a linear function that will generate on the analysed interval values calculated for the dependent variable, which in their entirety are positioned as close as possible to the real observed values. All observed points will be taken into consideration and will contribute in the same measure to minimizing the total of deviations reported to the calculated values, based on the future regression function.

In reality, the function should not pass as close as possible to all points, because not all points are important to the same degree for future predictions. We can include here some observation errors, the outliers' problem, or other exceptional situations in the phenomenon's evolution, and with a very small probability of ever occurring in the future. What criteria can we consider to select only a part of the observed points? Obviously, the regression purpose, meaning **a good prediction, should prevail** when choosing the points to be considered for the Support Vector Regression (SVR). Although the most frequently used for classification, SVM provides excellent results when it comes to regression too.

For a greater robustness of the predictor, the algorithm based on support vectors determines not a hyperplane but a hyper-tube in the continuous space that can encapsulate as many points as possible from the observations' set. In other words, keeping ε stationary – the tube's interior radius – we are looking for the direction in which we can include the largest number of observed points.

A natural question would be why we aren't looking for two hyper tubes given we have two classes, easily separable in a certain way, and to which correspond at least two big clusters of points. The question is further justified as we aim to introduce as many points as possible in the fixed dimension tube, and the only tube identified by SVR is centered precisely on the least densely populated area by points, which separates the classes! The answer is linked to the fact that we do not wish to favour any of the influence factors, but to highlight the measure in which their combined effect contributes to the outlining of the future categories of organizational culture.

Given that at a fixed ε it is not always possible to capture all x_i, we can also use here the slack variables ξ_i. When used, these come to mitigate the force of the restrictions regarding the pegged ε. The restrictions that are not tight do not influence the optimum point, meaning the deviations that are under the accepted ε deviation are not counted by the algorithm, and the associated points are not part of the support vectors, meaning those points that could improve the predictor's quality under the given conditions. Whilst in the SVM classification, we have only one slack variable category (ξ_i) for each point, the regression SVM needs two categories for the relaxation variables ξ_i and ξ_i*, for each point.

$$y_i - (w^T x_i + b\,) \leq \varepsilon + \xi_i$$
$$(w^T x_i + b\,) - \ y_i \leq \varepsilon + \xi_i^{\,*}$$
$$\xi_i, \xi_i^{\,*} \geq 0$$

This is explained by the fact that when it comes to classification, we are only interested if the point passed from the margin of its class to the other class (only one direction to avoid); with regression we also have the other extreme, meaning the point is placed in the right class but too deep to be caught by the regression tube (second direction to mitigate through relaxation variables)!

All four-point categories are illustrated in Figure 2 in relation to the ξ-tube.

The prediction needs to be understood at a phenomenon level as well as a qualitative class.

SVR comes with predictor robustness, controllable through the configuration parameters of the algorithm.

The algorithm is quite robust and tolerant to outliers, because the points inside the ε tube or placed at a large distance outside the tube do not influence the model. SVR is less sensitive to the data "noise".

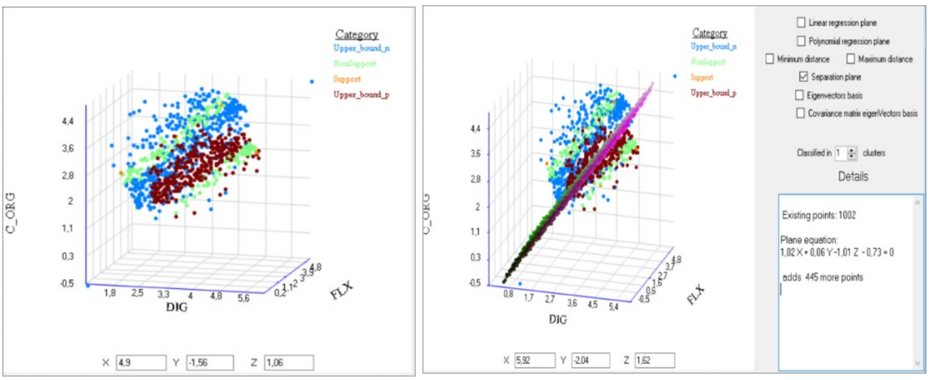

Figure 2. The role of observations in the estimation of the organizational culture evolution

a) Estimation hypertube b) Placement of the hypertube versus the separation hyperplane

Source: Results obtained from the authors' software.

5. Results and discussion

This section reports the empirical findings obtained by applying the methodology described in Section 4 to the 1,004 valid responses and discusses their implications. The results follow the analytical pipeline: the cultural typologies revealed by KNN clustering (Figures 1 and 2), the separation of organizations according to the predominance of the influence factors obtained with the SVM classifier, and the trajectory of cultural evolution estimated through SVR. The KNN clustering of the standardized scores in the three-dimensional space (organizational culture, digital-transformation intensity, and internal agility) produced several distinct agglomerations, presented and interpreted below.

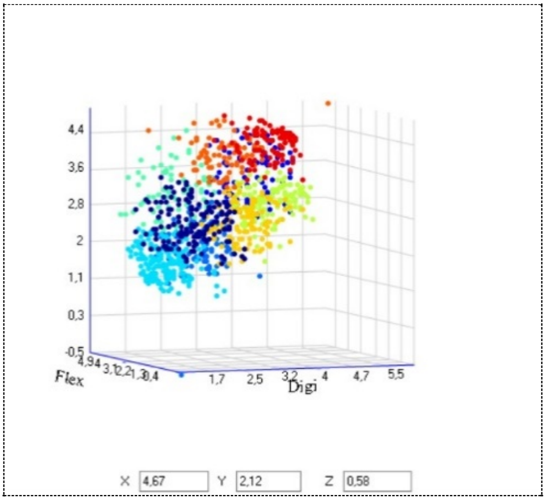

Figure 3. Organizational culture data projected in a three-dimensional space and the distribution of 10 clusters

Legend: each plotted point corresponds to one organization, positioned according to its standardized scores on the three axes — organizational culture (x), digital-transformation intensity (y) and flexibility to change (z). The ten colours denote the clusters returned by the K-Means algorithm, and the local density of the points reflects the concentration of organizations sharing a similar cultural profile; sparser regions indicate transitional or atypical profiles.

Source: Graphic resulting from the authors' software.

Along with the manner in which the data points cluster, an aspect just as important is represented by the density of the points in the multidimensional space; the shape of the points' repartition can provide a preliminary perspective in identifying the behavior classes of the companies, from the organizational culture perspective and the factors that support it. Figure 3 presents the first 10 points' agglomerations present in the data, determined by using the classic K-Means algorithm. Although some clusters do not seem representative enough from a volume perspective, we must take into consideration that regardless of the chosen perspective to represent some points in 3D, one of the dimensions is always less visible; the analysis has been done easily, through interactive visualization, so that through spinning in different directions, the human perception can realize the real dimension of each cluster.

Although this is possible only when working with a reasonable number of points, from our own experience, somewhere between 1,000 and 4,000, we must highlight the fact that even a random distribution of the points could synthesize well enough the internal structure of a much larger cloud of points.

Another utility of this study is also related to the identification of training possibilities of some learning models in view of recognizing the main categories of companies, based on their positioning concerning the organizational culture.

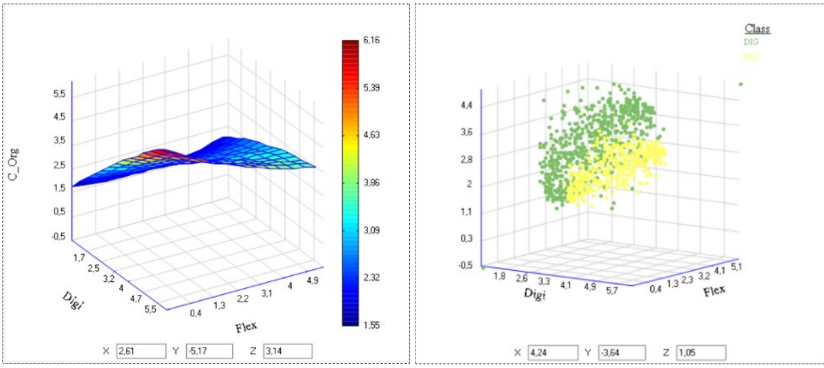

Figure 4. The impact of the digital transformation and flexibility to change on organizational culture

a) the perspective of the strength of organizational culture; b) the perspective of influencing factors

Source: Created with custom software developed by the authors.

Building on these typologies, the SVM classifier described in Subsection 4.3 separated the organizations into traditional and adaptive profiles with a wide, robust margin, confirming a strong association between digital maturity, agility, and adaptive cultures, while the SVR estimation in Subsection 4.5 indicated a gradual shift towards more flexible cultures with lower resistance to change. These findings remained stable in the presence of outliers and atypical observations, which supports the practical use of the proposed KNN-SVM-SVR pipeline for the early detection of cultural barriers in the Romanian and Eastern European context.

6. Conclusions

In the space generated by variables linked to the organizational culture, the digital transformation, and the degree of adaptability, the KNN algorithm clearly highlighted the natural grouping among entities, showcasing how differently the companies in the studied sampling are. Through the SVM method, the separation of the companies into precise classes has been well outlined – the crossover from classical structures is less flexible, towards typologies open to digital transformations, being heavily supported even when the data contained errors or extreme points. With the help of SVR, the future tendencies of the cultural evolution have been estimated without major difficulties; the model is correctly reproducing the complex interactions between the factors, predictions that remain stable in the face of unexpected variations, better than the standard approaches. In relation to the theory, the new combined model is increasing the knowledge base on the companies' culture evaluation, showing how the KNN-SVM-SVR hybrid is working better than old techniques, incapable of capturing the curvilinear relationships (Li et al., 2021; Schachner et al., 2024). As the research advances, this study is positioned where digital transformation meets adaptive algorithms, proving that the results can be generalized without losing clarity, unlike the fixed questionnaires, and remaining at the same time a testable structure in other management contexts (Murire, 2024).

In practice, the companies can use these tools as a quick evaluation means of the internal operations, thus opening the way to targeted interventions – such as training programs in digital skills or consolidation of the organizational agility – that contribute to the increase of employee involvement through better alignment with the internal values and the technological requirements. In the Romanian context, the public institutions' leaders or the private companies can capitalize on these solid predictions to diminish the change resistance, thus consolidating the team unity and the overall performance (Pelău, 2024; Stăneiu et al., 2024).

Although it provides valuable information, the research is confronted with certain structural weaknesses. The data based on the participants' reports can distort the results because of the tendency to provide socially acceptable answers. The participants are mainly from Romania, which limits the applicability of the conclusions in other cultural environments. Even though the observation of a group reduced in time brings analytical benefits, the short duration of the observation leaves significant gaps. The performance of the machine learning models might be linked to the volume of available data when adjusting the parameters. In situations with major changes of the given conditions, their precision could drop easily (Abiodun et al., 2018; Tian et al., 2012). Future analysis can explore texts from internal communications or Glassdoor reviews using semantic methods. The cultural nuances connected to the employee's departure could be better highlighted through an adapted deep learning. The longitudinal studies, even though they require time, are providing solid verification of these models. Eastern European contexts, compared to other regions, are unravelling subtle differences. Some ethical limitations appear when the predictions are based on sensitive data. The hidden biases in the algorithms must be identified before implementation. The research does not stop where efficiency appears.

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