Profiling Innovation Actors: Insights from Patentees Data for Intelligent Sustainable Development

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Abstract. Innovation actors play a pivotal role in sustainable development research. In spite of this, existing empirical studies often struggle to capture the full complexity of patentees' human attributes and motivational drivers. From prior work in organizational behavior and patenting dynamics, this paper introduces an integrated machine learning framework for patent-holder profiling that combines human resources (HR) data with survey-based measures of work motivation. We evaluate a diverse set of classification models, including logistic regression, random forests, gradient boosting, and support vector machines, across multiple behavioral prediction tasks. In addition, we assess how feature richness and principal component analysis (PCA)–based dimensionality reduction affect the trade-off between predictive accuracy and model interpretability. Results indicate that models augmented with motivational survey features consistently outperform HR-only benchmarks, while PCA offers an effective pathway to parsimonious representations with limited performance loss. In summary, the contributions of this work are a systematic comparison of machine learning techniques for profiling innovation actors, a demonstration of the added value of human-centered motivational data, and some practical insights for the deployment of explainable AI in Intelligent Sustainable Development (ISD).

Keywords: Sustainable Development · Machine Learning · Innovation · Model Interpretability

1 Introduction

Sustainable development heavily depends on understanding the human actors behind innovation, especially when patenting activity signals technological change with social and environmental consequences. Recently technical literature has highlighted the need for more insightful behavioral profiles of patentees

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O. Gervasi et al. (Eds.): ICCSA 2026 Workshops, LNCS 16762, pp. 277–289, 2027.
https://doi.org/10.1007/978-3-032-30524-4_18

and the potential of data-driven methods to reveal the motivations and capabilities that lead to innovation [1–4,6–11,13–16]. In this context, innovation actors are way more than just inventors and patent filers, but also individuals whose organizational, demographic, and motivational attributes shape the design and adoption of novel technologies.

However, past studies often focused on either structural patent data or limited statistical summaries, leaving a gap in the integration of diverse machine learning approaches with human-centered survey evidence. Some of these studies suggested that work motivation, job characteristics, and HR-related (i.e., personal and institutional) information are relevant to innovation outcomes. However, the relative value of different classifiers and the impact of data analysis methods such as dimensionality reduction have remained underexamined. This gap is evident in the literature in the context of ISD, whose policies are relevant as much as the they exhibit properties such as explainability and model transparency.

This manuscript builds on prior research [7,8] by incorporating more machine-learning methods and techniques for profiling patentees and by explicitly comparing their performance on multiple classification tasks. Using an original dataset that integrates structured human-resources data with responses from a work-motivation survey, the study assesses how this multimodal approach enhances both predictive performance and interpretability. In addition, PCA-based dimensionality reduction is examined for preserving the most informative behavioral components while mitigating feature complexity.

Informed by the findings of the earlier studies and the requirements of explainable AI, this work aims to show that richer feature representations combined with deliberate model selection can generate more robust and actionable insights for ISD. The findings are intended to guide both practitioners and researchers in identifying modeling strategies that achieve an effective balance between predictive accuracy, transparency, and practical applicability.

The remainder of the paper is organized as follows. Section 2 reviews related work on innovation actors, sustainable development, and machine learning for behavioral profiling. Section 3 describes the dataset and motivations for combining HR and motivation data. Section 4 presents the methodology, including dataset construction, feature extraction, and model evaluation. Section 5 reports the experiments and results. Finally, Sect. 6 concludes with key findings and directions for future research.

2 Related Work

Research on patenting motivation and innovation actor profiling has advanced notably with Jesus et al. [7], who analyzed Brazilian university researchers' motivational factors for patenting, and Jesus et al. [8], who proposed a classification model for patenting motivation in Brazilian public universities. Jesus et al. [7] explores how intrinsic and extrinsic motivators interact with institutional incentives, while Jesus et al. [8] moves this research one step further by operationalizing motivation markers in a supervised learning framework. These foundational

studies establish the empirical and methodological baseline that this manuscript extends by adding a broader comparative evaluation of classifiers and richer human-centered and PCA-based feature sets. More than just improving predictive performance, this work also seeks to enhance the interpretability of models for ISD applications, where understanding the human and organizational drivers of innovation is crucial for policy design.

Broader studies of academic and university innovation confirm the importance of institutional incentives and actor-level characteristics. Baldini [1] examine university strategies for encouraging patenting through policy design and incentive mechanisms, while Dalmarco et al. [4] document how organizational ecosystems and managerial choices shape technology-transfer trajectories. Blind et al. [2] and Good et al. [5] highlight the tensions between academic publishing, technology transfer, and patent-driven innovation, pointing to the complex role of academic norms in shaping innovation behavior. Similarly, Lam [9], Moutinho et al. [11], Perkmann et al. [13] provide complementary evidence on individual-level drivers, such as career incentives, professional networks, and engagement with intellectual property.

The human and motivational dimensions of innovation are well represented in the literature. Jesus et al. [7] provides additional evidence on motivational constructs by comparing diverse survey measures, while Choi et al. [3], Issah et al. [6], Moletta and Pilatti [10], Ponta et al. [14], Rossoni et al. [16] examine motivational dimensions, barriers, and identification strategies that shape innovation activity across sectors. These studies collectively demonstrate that motivation is multifaceted, shaped by both personal aspirations and structural conditions, and that capturing it requires more than patent counts or bibliometric indicators.

At the intersection of data science and innovation studies, Choi et al. [3], Jesus et al. [8], Ponta et al. [14] show how classification models can identify innovation-related behavior from structured variables, while Issah et al. [6] emphasizes the need for systematic reviews and clearer interpretability in machine learning applications. Potekhina [15] and Blind [12] discuss the implications of technology use and organizational choices for innovation outcomes, and Torrisi et al. [17], Veer and Jell [18] examine contribution patterns in collaborative environments that are relevant to how innovation actors interact within research teams.

In summary, technical literature supports employing comprehensive machine learning modeling for innovation actors, but also suggests that this idea is yet to be fully explored. Existing work has documented the importance of motivation, institutional incentives, and actor-level characteristics, but it has rarely combined machine learning comparisons, HR information, and survey-derived motivation data in the same framework. The present study builds on these contributions by integrating HR variables, motivation survey data, and a comparative suite of predictive algorithms in the context of Intelligent Sustainable Development. This approach aims to deepen our understanding of how diverse data sources can improve both predictive performance and interpretability for profiling innovation actors.

3 Dataset

The dataset used in this manuscript is a subset of original sample employed in the prior works by Jesus et al. [7] and Jesus et al. [8]. It consists of Brazilian public university patentees and researchers whose administrative HR records were linked to a tailored survey on work motivation, organizational support, and innovation-related perceptions. The dataset includes demographic and employment attributes, patenting experience and outcomes, institutional affiliation, and psychometric measures for intrinsic/extrinsic motivation, perceived incentives, and barriers to innovation.

The original sample was collected through a combination of web-scraped data from publicly available resumés of patentees affiliated to major Brazilian universities as well as their answers to the aforementioned survey questionnaire. A total of 450 patentees were invited to participate, and 131 agreed to that, so that only 131 full records were considered for this study: such a relatively small and context-specific sample limits the generalizability of any analysis of it, but it plays an important role given the lack of comprehensive datasets in this context. Table 1 enumerates which HR-related input variables were ultimately used. Besides these, 27 additional input variables were derived from the survey responses, provided as 1-to-5 Likert-scale indicators.

With respect to the target variables, the study focuses on several key categorical attributes derived from the survey responses that capture the patentees' engagement in patenting activities, professional orientations, motivational drivers, and value alignments. These variables provide insights into the behavioral profiles of innovation actors. Table 2 summarizes the distribution of values according to their respective counts for each target variable analyzed in the dataset. The original classification of each patentee into these categories resulted from the application of conceptual rules on their survey responses [7,8]. Ultimately, assessing the ability to learn these rules from all available input variables or even the HR-related subset alone is one of the main objectives of this study.

4 Methodology

This study follows a supervised multi-class classification workflow to profile innovation actors from heterogeneous inputs that combine HR attributes and motivation-related survey indicators. Let $\mathbf{x}_i \in \mathbb{R}^d$ denote the feature vector of patentee i and y_i its categorical target label for one of the four behavioral outcomes introduced in Table 2. The objective is to learn a mapping $f : \mathbf{x} \mapsto y$ that generalizes across distinct target structures and class distributions while remaining informative for ISD-oriented decision support.

Table 1. Key input variables from the patentee dataset and their measurement types.

Input Variable	Type
Full articles published in journals	Numerical
Published book chapters	Numerical
Complete papers published in conference proceedings	Numerical
Abstracts published in conference proceedings	Numerical
Number of patents and registration requests	Numerical
Bachelor's degree location	Categorical
Master's degree location	Categorical
Doctorate's degree location	Categorical
Birth Interval	Categorical
Gender	Categorical
Birthplace	Categorical
Have you ever had a patent awarded?	Categorical
Have you ever had any patents licensed?	Categorical
Have you ever had a patent deposited abroad through Patent Cooperation Treaty (PCT)?	Categorical
Have any patent request been the result of interaction with the industry?	Categorical

Table 2. Summary of target variables values and their counts.

ID	Variable	Value	Count
1	Interaction in patenting process. Active or passive?	Active	59
		Passive	72
2	Classification regarding professional orientation	Hybrid	72
		Entrepreneurial	44
		Pragmatic traditional	11
		Pure Traditional	4
3	Nature of motivation	Extrinsic	44
		Mixed	44
		Intrinsic	43
4	Relationship between standards / personal values	Identification	55
		Introjection	34
		Integration	42

The methodological design is organized around four target variables: interaction in the patenting process, professional orientation, nature of motivation, and relationship between standards and personal values. For each target variable, we compare a diverse set of learning paradigms, including linear (Logistic

Regression), probabilistic (Gaussian Naive Bayes), kernel-based (Support Vector Machines), tree-based (Decision Trees), and ensemble models (Random Forests, Gradient Boosting, Voting Classifier combining Logistic Regression, Random Forest, and Gaussian Naive Bayes). Each of the considered classification models were subject to grid search for hyperparameter optimization, and were assessed through standard k-fold cross-validation on the same data splits.

To examine how predictive performance responds to feature availability, we define experimental scenarios along two binary dimensions: feature scope (full feature set versus an HR-only subset) and feature representation (original variables versus PCA-transformed features). PCA is employed as a linear projection technique to evaluate whether compact representations can retain discriminative capacity while alleviating variance inflation and reducing the risk of overfitting. The full feature configuration integrates both HR and survey-based information, while the HR-only setting restricts the input space to administrative and demographic attributes.

Model performance is evaluated using a complementary set of metrics, including Accuracy, Balanced Accuracy, Precision, Recall, and F1 score. This metric suite enables a nuanced assessment under class imbalance, which is particularly relevant for multi-class problems involving minority groups. Balanced Accuracy and macro-averaged measures are emphasized to prevent overly optimistic estimates driven by dominant classes.

Rather than focusing solely on pointwise metric outcomes, the analysis highlights performance distributions across targets, experimental scenarios, and model architectures. Results are therefore summarized using boxplot-based comparisons, which capture central tendencies, dispersion, and outlier behavior, offering insight into model stability and consistency. This approach supports three complementary analytical perspectives discussed in Sect. 5: sensitivity across targets, convergence across performance metrics, and robustness across architectures.

Finally, interpretability is addressed through feature-importance analyses conducted on representative models, enabling consistency checks between learned decision patterns and established conceptual assumptions. This component is particularly critical for ISD contexts, where transparency and traceability are essential for translating machine-learning outputs into actionable guidance for policy and institutional decision-makers.

5 Experiments

This section presents a structured empirical analysis of the proposed profiling pipeline under different feature-space constraints. First, we examine how predictive performance varies across the four target variables when toggling HR-only feature subsets and PCA-based dimensionality reduction (Sect. 5.1). Next, we assess the stability and convergence of evaluation metrics to verify whether performance changes are consistent across accuracy- and balance-oriented criteria (Sect. 5.2). Finally, we compare model architectures to identify which learning

paradigms are more robust under information-rich and information-constrained scenarios (Sect. 5.3). For the sake of reproducibility, the source code used in this study is available at a public repository[1] or upon request. It was implemented in Python using well-known data science libraries (e.g., scikit-learn, pandas, seaborn). Any details regarding the specific hyperparameter values and other similar aspects can be found in the codebase.

5.1 Analysis of Performance Across Target Variables

The boxplots presented in Fig. 1 delineate the aggregated empirical performance distributions of all considered classification models across four distinct target variables, specifically examining the sensitivity of these models to feature subsetting (HR-only) and linear dimensionality reduction (PCA).

In the control scenario (HR-only: False, PCA: False), the models utilize the full feature space. A significant finding is the near-perfect performance attained for target 1 (Interaction in the patenting process), with scores consistently converging at unity. This was to be expected because the conceptual rule used to define this target variable is very simple; it only depends on the question, "Have any patent requests been the result of interaction with the industry?" binary input variable. So, this could be seen as a way to check the dataset and the modelling pipeline for sanity. On the other hand, Targets 2, 3, and 4 show a lot of variation, which means they are more sensitive to certain model architectures and hyperparameter settings when given the full set of features.

Introducing PCA under the full-feature configuration (HR-only: False, PCA: True) projects the data into a reduced orthogonal space. Such a transformation reduced the interquartile range (IQR) for Targets 2 and 3, whereas the opposite effect happened for Targets 1 and 4. Besides Target 2, all targets exhibit an overall decline in performance. These findings indicate that although the principal components is sufficient to preserve baseline predictive capacity, certain idiosyncratic features, particularly those relevant to minority classes, are likely discarded.

The shift to the HR-only feature configuration without PCA (HR-only: True, PCA: False) constitutes a substantial reduction in domain-specific information. The performance distributions show a downward shift in Targets 2 and 4 median, and an even stronger degradation for Target 3: this is an evidence that "Nature of motivation" is harder to infer from common HR data, so that public policies aiming to foster intrinsic motivation for patenting may require more specific data collection and monitoring strategies. This decline supports the idea that non-HR features, especially those capturing technical or procedural aspects of patenting, contribute essential discriminative information absent from the restricted HR-only subset. Target 1 remains an exception, sustaining high performance levels, as its defining predictor resides entirely within the HR domain.

[1] https://github.com/rafaeluft/MLPatenteesProfiles.

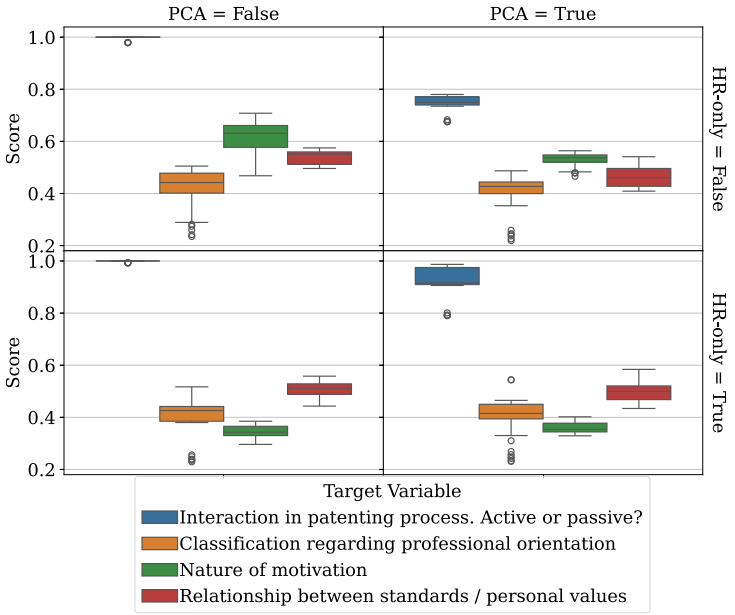

Fig. 1. Empirical Performances across Target Variables, aggregated over classifiers and evaluation metrics.

The most constrained experimental condition (HR-only: True, PCA: True) shows the compound information loss: the intersection of feature filtering and dimensionality reduction that could create a "bottleneck" effect, so that the reduced feature space could be insufficient to resolve the complexities of classification for subjective concepts represented by variables like 'Nature of motivation'. However, it can be observed the similarity of this scenario with its neighbors. The most evident difference regards target 1, since there is an increase in the performance compared to the other one with PCA = True, but a decrease compared to the other one with HR-only = True, suggesting that the effect of PCA on the larger feature space leads to a greater dillution of the discriminative power of the known predictor for this target variable.

5.2 Analysis of Evaluation Metric Stability

Figure 2 illustrates the stability and distribution of the considered performance metrics (Accuracy, F1-Score, Precision, Recall, and Balanced Accuracy) across the experimental pipeline. The analysis focuses on metric convergence and the impact of data transformations.

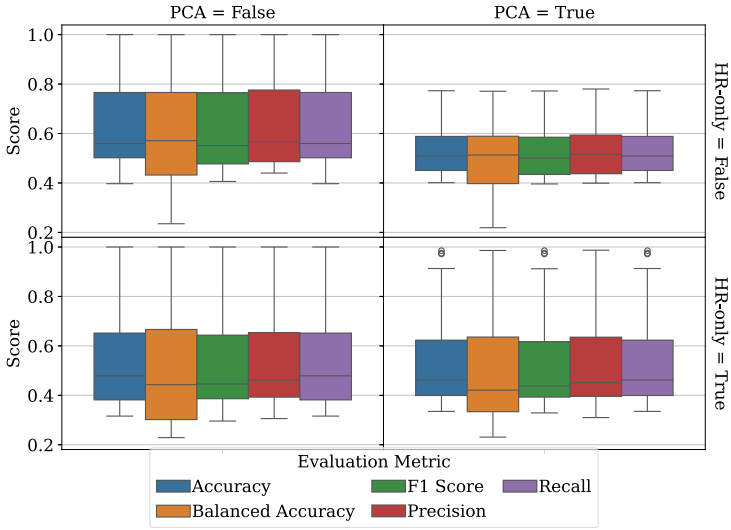

Fig. 2. Quantitative Assessment of Evaluation Metric Stability across Experimental Constraints

A key observation in the baseline configuration (HR-only: False, PCA: False) is the resemblance between evaluation metrics. The close alignment between Accuracy and Balanced Accuracy suggests that the target variables do not suffer from pronounced class imbalance that would otherwise inflate naive accuracy estimates. The substantial overlap in interquartile ranges (IQRs) for Precision, Recall, and F1-score indicates that the classifiers sustain a well-balanced trade-off between sensitivity and specificity.

When Principal Component Analysis is applied while retaining the full feature set (HR-only: False, PCA: True), a slight reduction in metric dispersion is observed, without a corresponding shift in median performance levels. The resulting metric stability suggests that the linear projection preserves the core decision boundaries, even as it suppresses minor feature-level variations that contribute primarily to extreme performance outliers in the unreduced feature space. The general pattern implies that the principal components adequately capture the effective dimensionality required for discrimination.

In contrast to dimensionality reduction, the restriction to HR-only feature subsets (HR-only: True, PCA: False) induces a systemic downward shift in the entire metric distribution. While the metrics remain tightly grouped, indicating that the models still function consistently within the limited information space, the overall predictive capacity is significantly curtailed. This performance decay suggests that the excluded technical and procedural metadata contain high-order discriminative signals that are non-redundant with the HR-only features.

The most constrained experimental condition (HR-only: True, PCA: True) illustrates the "information bottleneck" effect. Here, we observe the lowest median scores coupled with a higher degree of spreading over all metrics. This

convergence at a lower performance plateau implies that the combination of feature subsetting and linear transformation removes the necessary complexity required for high-fidelity classification. However, the existence of high-performing outliers in this quadrant suggests that for certain model architectures it is easier to overcome the explicit loss of feature diversity than the implicity loss of information through PCA, which may indicate that the latter is more detrimental to the preservation of critical discriminative signals than the former.

5.3 Comparative Evaluation of Model Architectures

Based on Fig. 3, the following analysis examines the performance variance and robustness of diverse classification algorithms (ranging from linear models to ensemble methods) across the experimental design space.

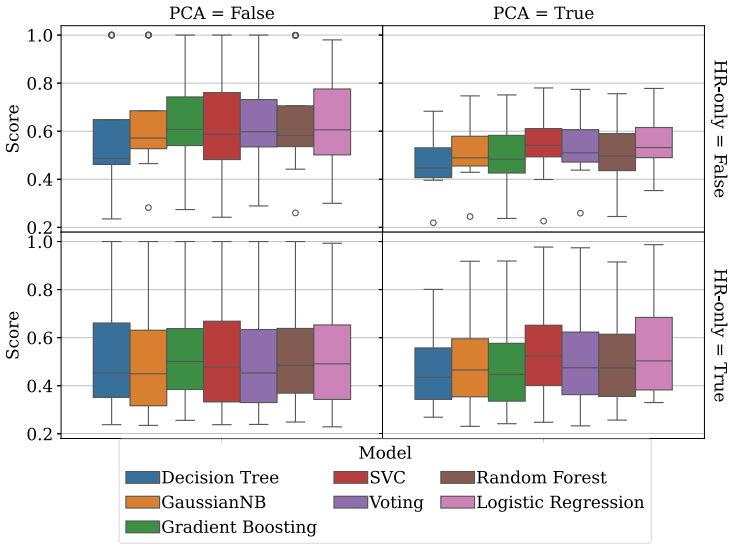

Fig. 3. Quantitative Assessment of Evaluation Metric Stability across Experimental Constraints

In the unconstrained configuration (HR-only: False, PCA: False), a pronounced divergence in model performance becomes evident. Ensemble approaches, most notably Random Forest and Gradient Boosting, achieve a substantially higher performance ceiling than linear baselines such as Logistic Regression. This pattern indicates that the full feature space encodes non-linear relationships and higher-order interactions that are more effectively leveraged by tree-based architectures than by purely linear models.

When PCA is applied while retaining the full feature set (HR-only: False, PCA: True), it functions as a regularization mechanism, particularly for models prone to high variance. Although peak performance levels remain largely

unchanged, the interquartile ranges for architectures such as Decision Trees tend to contract. This compression suggests that the projection onto a lower-dimensional orthogonal space attenuates noise that would otherwise encourage overfitting, yielding more stable performance across folds and targets.

Constraining the input space to HR-only features without dimensionality reduction (HR-only: True, PCA: False) produces a marked reordering of the model hierarchy. In this information-limited setting, the performance gap between complex ensemble methods and simpler models diminishes. This convergence implies that once key discriminative features are removed, the benefits of sophisticated inductive biases are reduced, and overall predictive capacity becomes bounded primarily by signal scarcity rather than architectural expressiveness.

In the most restrictive scenario (HR-only: True, PCA: True), Logistic Regression and Support Vector Classifiers often exhibit stability comparable to or exceeding that of ensemble methods. This outcome underscores that in low-dimensional, feature-constrained spaces, simpler models with strong regularization tend to be more resilient to information loss, whereas more complex architectures may struggle to identify meaningful decision boundaries in highly compressed representations.

6 Conclusion

This study introduced and empirically evaluated a machine-learning framework for profiling innovation actors through the integration of structured HR data and survey-based motivational information. The results demonstrate that model performance is strongly dependent on feature richness: settings with comprehensive information generally achieve higher and more discriminative predictive outcomes, whereas HR-only configurations introduce a clear performance bottleneck, particularly for targets reflecting more subjective behavioral constructs. Dimensionality reduction via PCA can enhance compactness and stability in selected scenarios; however, its effectiveness is contingent on target complexity, as it may also attenuate class-specific variability that supports discrimination.

Comparative analyses further reveal that ensemble and non-linear architectures consistently benefit from feature-rich representations, while simpler models become increasingly competitive as the feature space is constrained. This finding underscores an important methodological implication for ISD research: model architecture should not be selected independently of feature-space design. Moreover, the combined use of accuracy-based and balance-aware evaluation metrics proved essential for avoiding distorted interpretations in multi-class problems characterized by uneven class distributions.

The contributions of this work are threefold. First, it provides a structured benchmarking of diverse classifiers across multiple behavioral targets. Second, it offers empirical evidence for the predictive relevance of human-centered motivational variables in innovation profiling. Third, it presents an interpretable analytical pipeline that integrates performance distribution analysis with feature-importance reasoning. Collectively, these contributions offer actionable guidance

for researchers and practitioners seeking explainable approaches to profiling innovation actors.

Naturally, there are some limitations to be considered. The dataset is of moderate size and context-specific, and target labels are constructed from conceptual rules applied to survey responses, which may limit external validity. Future research should therefore seek to extend the analysis across institutions and time horizons, explore alternative representation-learning techniques beyond linear PCA, and incorporate calibration and uncertainty analyses to enhance the robustness and reliability of decision support in operational ISD settings.

Acknowledgments. This work has been funded by national funds through FCT–Fundação para a Ciência e a Tecnologia, I.P., through project UIDB/05037/2025 with DOI 10.54499/UIDB/05037/2025.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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