Editorial

Inaugural Editorial of the Inspire Intelligence First Issue Publication

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Artificial Intelligence (AI) has rapidly evolved into a key technology that affects decision-making in healthcare, analytics, and operational systems. Machine learning and deep learning have advanced significantly, enabling predictive modeling frameworks to learn from large, complex, and messy real-world data. You can use these frameworks for tasks such as predicting disease risk, diagnosing medical images, and forecasting operations [1]. These advancements have shown significant improvements in accuracy and efficiency, especially through time-series analysis and ensemble learning methods that identify temporal dependencies and diverse data patterns.

AI-powered clinical decision support systems have shown promise in healthcare by improving the accuracy of diagnoses, streamlining care pathways, and allowing for earlier intervention. Deep learning models used in medical imaging and healthcare analytics are now getting close to or even better than expert-level performance in some tasks. But as these systems become more complicated, people are worried about transparency, accountability, and clinical trust, especially in high-stakes situations [2].

As a result, Explainable Artificial Intelligence (XAI) and model interpretability have become important tools for responsible AI use [3]. Interpretability methods help ensure that AI outputs are useful, can be checked, and are in line with what experts in the field know. In addition to technical performance, the increasing focus on human-centered AI underscores the necessity to address workforce adaptation, usability, and well-being as intelligent systems transform professional roles and organizational frameworks. Current research underscores that sustainable AI innovation relies not solely on predictive capabilities but also on interpretability, real-world applicability, and human-centered design [4].

The first contribution in this issue addresses a critical yet underexplored problem in intensive care (ICU) practice: the high frequency of phlebotomy required for patient monitoring and its substantial contribution to iatrogenic anemia, a condition affecting most ICU patients. Conventional blood sampling methods are still primarily reactive and do not have the ability to predict the total number of blood samples needed during an ICU stay. The authors use Long Short-Term Memory (LSTM) architecture to model the temporal dynamics of patient data available at ICU admission, including physiological measurements, laboratory values, and demographic characteristics, to overcome this limitation. A comprehensive framework for predicting blood draw frequency as a longitudinal outcome is presented in this work. The model's capacity to capture heterogeneity in patient trajectories is improved by the introduction of a novel loss function intended to handle variable-length, multi-output sequences. The outcomes support the viability of proactive phlebotomy planning by showing encouraging predictive performance

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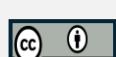
on actual ICU data. According to the study's findings, incorporating temporal deep learning models into ICU workflows may improve patient outcomes by reducing needless blood draws, personalizing monitoring strategies, and reducing avoidable complications like iatrogenic anemia.

The second contribution in this issue tackles the ongoing difficulty of correctly differentiating benign from malignant breast lesions. This task is crucial for early diagnosis and better clinical outcomes, but it is still constrained by the limitations of conventional imaging modalities. While digital mammography (DM) continues to be the clinical standard, its predominantly structural information may restrict the performance of deep learning–based classifiers. The authors use a comparative deep learning approach to overcome this constraint, training a ResNet-18 convolutional neural network on both DM and contrast-enhanced spectral mammography (CESM), which offers complementary functional imaging data. The study's methodology includes rigorous evaluation using stratified cross-validation, blind testing, and SHapley Additive exPlanations (SHAP) model interpretability analysis, which evaluates both predictive performance and the clinical plausibility of model decisions. The findings show that CESM performs significantly better than DM in the classification of malignant lesions, achieving higher AUC values across several evaluation metrics and generating more targeted and anatomically significant attribution maps. These results imply that the accuracy and interpretability of CNN-based models are improved by the additional functional information in CESM. The study acknowledges the ongoing value of DM as a contrast-free screening tool when CESM is unavailable but concludes that CESM-integrated AI systems hold significant promise for dependable clinical deployment, particularly in detecting malignancies.

The third contribution acknowledges the limitations of depending solely on clinical or genetic data and tackles the persistent public health challenge of accurately identifying people at risk of diabetes using scalable and accessible data sources. Using extensive surveys and clinical data from the National Health and Nutrition Examination Survey (NHANES), the authors use a machine learning-based approach to address this issue. They build a binary classification framework based on reported diagnoses and objective plasma glucose measurements. The analysis produces a small set of 16 variables that strike a balance between model complexity and practicality by prioritizing clinically relevant and interpretable predictors through systematic feature selection. In addition to an ensemble approach intended to capitalize on complementary model strengths, several individual machine learning models are assessed. Although Gradient Boosting, the best individual learner with a strong AUC of 0.84, outperformed the ensemble approach, decision-threshold optimization significantly improved recall for diabetic cases. The results show that survey-derived data can support reliable disease risk modeling and they show how well tree-based models predict diabetes. The research concludes that employing machine learning methodologies on population-level data can facilitate the early identification of diabetes and inform targeted public health initiatives for disease prevention and management.

The fourth contribution illustrated the importance of predictive modeling in the fields of public health and healthcare, where trade-offs between practical deployment, interpretability, and accuracy are crucial. Contribution 4 covers the operational context of last-mile logistics. Contribution 4 primarily discusses the challenge of producing accurate demand forecasts in settings characterized by erratic consumer behavior and strict operational limitations. Inaccurate forecasts can result in inefficiencies, higher expenses, and detrimental effects on sustainability. To overcome this difficulty, the authors use a comparative modeling approach, comparing a modified transformer-based architecture (GPT-2) that can capture intricate and nonlinear demand patterns with a transparent, additive time-series model (Prophet). The models are evaluated in several areas, such as forecast accuracy, robustness to volatility, computational efficiency, and sustainability considerations, using real-world delivery data and systematic hyperparameter optimization. The findings show that while GPT-2 demonstrates better adaptability in extremely volatile environments, albeit with higher resource requirements, Prophet performs robustly in stable demand scenarios because of its interpretability and low computational overhead. To provide a practical framework for integrating AI-driven forecasting solutions in last-mile delivery systems, the study

concludes that no single model is always best. Instead, model selection should be guided by operational context, balancing predictive performance with explainability and resource constraints.

The fifth contribution in this issue draws attention to the frequently disregarded human effects of AI integration, which complement the other contributions that concentrate on using AI to optimize performance and decision-making. The main issue discussed is the increasing psychological strain that companies are placing on workers as they implement AI technologies and demand ongoing skill development without corresponding changes to workload or institutional support. The study takes a conceptual and analytical approach to investigate the relationship between technological change, learning demands, and workplace well-being instead of using a technical modeling framework. The study emphasizes how inadequate adaptation time and ongoing performance pressures worsen detrimental mental health outcomes by combining observations on stress, anxiety, burnout, and decreased motivation. The analysis underscores that the application of AI-driven changes within organizational structures, rather than AI itself, is the root cause of these difficulties. The study emphasizes that human-centered considerations are crucial for the long-term success of AI-enabled workplaces by concluding that sustainable adoption of AI requires intentional workload management, encouraging training environments, and organizational policies that prioritize employee well-being alongside productivity.

These studies demonstrate the breadth of AI applications and the common challenges that accompany their deployment, including interpretability, contextual suitability, and human impact. They demonstrate the necessity of developing AI solutions that are not only accurate and efficient but also transparent, domain-sensitive, and sustainable, thereby ensuring that technological progress translates into meaningful and responsible real-world benefits.

We thank the authors of these articles. We anticipate these articles will add positively to the current body of knowledge.

List of Contributions:

1. Al Mallah, R., & Quintero, A. (2026). Toward improved ICU care: Phlebotomy frequency using deep learning. *Inspire Intelligence, 1*(1), 1-9.
2. Acosta-Jiménez, S., Mendoza-Mendoza, M. M., Galván-Tejada, C. E., Celaya-Padilla, J. R. D.-C., & Galván-Tejada, J. I. (2026). Interpretable deep learning for breast lesion classification: A SHAP-based comparison of CESM and digital mammography. *Inspire Intelligence, 1*(1), 10-28.
3. Mabkhout, H., & Benhra, J. (2026). Prophet and GPT-2 algorithms for demand forecasting in last-mile delivery: A comparative analysis and optimization. *Inspire Intelligence, 1*(1), 29-41.
4. Patel, P. (2026). Enhancing diabetes prediction through ensemble machine learning models on survey-based and clinical data. *Inspire Intelligence, 1*(1), 42-51.
5. Ranjan, B., Sivanesan, I., & Bernie, S. B. (2026). Artificial intelligence and anxiety: The human price of adapting to a smarter workplace. *Inspire Intelligence, 1*(1), 52-67.

References

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