ARTICLE SUMMARY 4 : 3 AI algorithms for understanding business process automation results

Business Process Modeling and Automation: Businesses use techniques like BPMN and DMN to represent, abstract, and automate tasks. These standards enable the formal representation, verification, testing, and simulation of complex workflows.Black-box Predictive Models: In AI/ML, black-box models make inputs and outputs observable but hide their internal functions, making it difficult to understand why certain predictions are made.

Explainable AI (XAI): XAI encompasses methodologies and algorithms to produce human-understandable explanations for black-box models. It includes intrinsic methods to simplify models and post-hoc methods to explain already-trained models. Local Interpretable Model-Agnostic Explanations (LIME): LIME perturbs the original data to understand the importance of features and their impact on predictions in a local context.

Shapley Additive explanations (SHAP): SHAP utilizes Shapley values from game theory to understand the contribution of individual features to predictions. It addresses the combinatorial explosion and missing inputs issues by using a SHAP kernel.

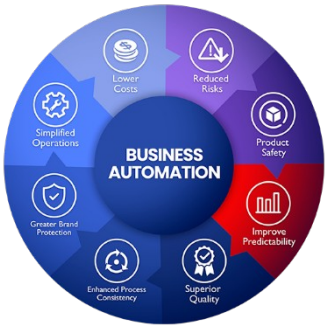
Counterfactual Explanations: Counterfactual explanations provide alternative input scenarios that lead to desired outcomes. They focus on properties like validity, sparsity, and actionability to ensure meaningful and interpretable explanations.

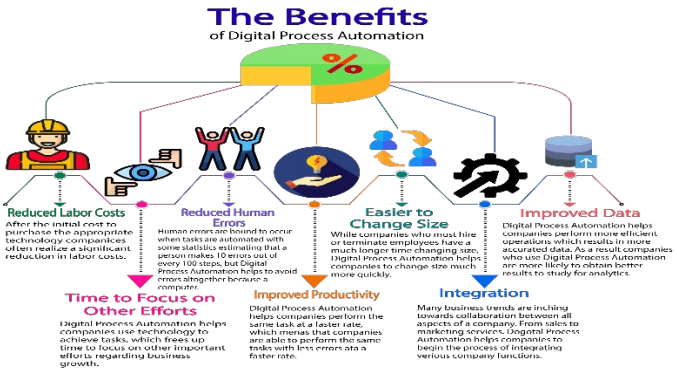
In summary, these techniques and methodologies aim to make complex models more interpretable and trustworthy by providing insights into their decision-making processes.

Global vs. Local Explanations: Explanations can be either global, providing insights into a model's general behavior, or local, focusing on a specific prediction or instance. Local explanations are often preferred as they offer more contextually relevant insights.

Model-specific vs. Model-agnostic Methods: Explainability techniques can be tailored to specific models or designed to work across various model architectures. Model-agnostic methods provide flexibility and can be applied to any model type.

Ethical Considerations: Understanding and explaining AI decisions are not just technical challenges but also ethical imperatives. Transparent AI systems can help mitigate bias, ensure accountability, and foster trust among users and stakeholders.





In conclusion, explainability methods play a vital role in making AI systems more transparent, accountable, and trustworthy, thereby facilitating their adoption and acceptance across various domains and applications.