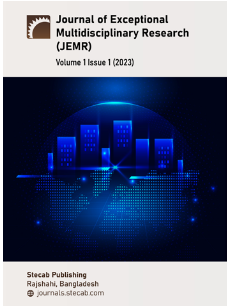

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The Role of Metadata in Promoting Explainability and Interoperability of AI-based Prediction Models

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About Article

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ABSTRACT

This systematic literature review delves into the critical role of metadata in enhancing the explainability and interoperability of AI-based prediction models. As AI technologies permeate various sectors, the need for transparent and coherent predictive models becomes increasingly vital. Metadata, which refers to structured information that contextualizes data, serves as a pivotal component in achieving this transparency and coherence. This review synthesizes 50 existing literature to evaluate how different types of metadata—such as descriptive, structural, and administrative metadata—contribute to the understanding and integration of AI models, thereby facilitating better decision-making and trust in AI systems. The review identifies key themes related to the challenges of explainability, including the complexity of AI algorithms and the opacity of model outputs, and discusses how robust metadata frameworks can mitigate these issues by providing essential context and clarity about model decisions. Furthermore, it examines the significance of interoperability in AI applications, highlighting how standardized metadata can enable seamless integration across diverse systems and platforms. The findings underscore the necessity of developing comprehensive metadata strategies to enhance both the interpretability of AI predictions and the compatibility of AI systems across different environments. Ultimately, the review calls for continued research into metadata standards and practices that can promote a more reliable and user-friendly AI landscape.

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1. INTRODUCTION

AI-based prediction models, which utilize algorithms and statistical techniques to forecast outcomes based on historical data, have become integral to decision-making processes across various industries, including healthcare, finance, and marketing (Abdulganiyu *et al.*, 2023; Mohsen, 2023). These models are designed to analyze complex datasets and provide insights that can optimize operations, enhance customer experiences, and improve overall efficiency (Mohsen, 2023; Elsken *et al.*, 2019). For instance, in healthcare, predictive models can identify patients at risk of certain conditions, enabling timely interventions that can save lives and reduce costs (Cica *et al.*, 2020). Despite its widespread adoption, AI-based prediction models face significant challenges related to explainability and interoperability. Explainability refers to the degree to which an AI model's decisions can be understood by human users, which is paramount for building trust and ensuring accountability (Abdulganiyu *et al.*, 2023). Many AI algorithms, especially those based on deep learning, operate as "black boxes," where the decision-making process is not transparent, leading to skepticism among stakeholders (Cica *et al.*, 2020). This lack of transparency can hinder the adoption of AI technologies, as users may be reluctant to rely on models whose predictions it cannot comprehend (Mikalef *et al.*, 2021; Sarker, 2022) Interoperability, on the other hand, pertains to the ability of different AI systems and models to communicate and function together effectively (Cica *et al.*, 2020). In practice, achieving interoperability is complicated by the diversity of data formats, standards, and protocols used across various platforms. This fragmentation can result in inefficiencies, data silos, and challenges in integrating AI solutions into existing workflows, ultimately limiting its potential impact (Monsalve *et al.*, 2023). Therefore, addressing these challenges is critical to maximizing the effectiveness and usability of AI-based prediction models.

The aim of this review is to explore the role of metadata in promoting the explainability and interoperability of AI-based prediction models. Metadata, defined as data that provides information about other data, can enhance the comprehensibility and integration of predictive models by offering context, definitions, and relationships among data elements. By investigating how structured metadata can facilitate clearer communication of model outputs and enable better alignment between different AI systems, this review aims to underscore the importance of metadata in overcoming the barriers to effective AI implementation.

2. LITERATURE REVIEW

2.1. AI-based prediction models

AI-based prediction models are computational frameworks that leverage machine learning algorithms to analyze historical data and forecast future outcomes. These models are designed to identify patterns and relationships within data, enabling them to make informed predictions about unseen instances (Mikalef *et al.*, 2021; Sarker, 2022). The applications of AI-based prediction models span a wide range of sectors, including healthcare, finance, marketing, and manufacturing. In healthcare, predictive models are utilized to forecast patient outcomes, optimize treatment plans, and manage resources effectively. For instance, models can predict the likelihood of hospital readmissions, allowing healthcare providers to implement preventive measures (Liao & Yao, 2021). In finance, AI models are employed for credit scoring, fraud detection, and stock market predictions, helping institutions make data-driven decisions that mitigate risks and enhance profitability (Mohsen, 2023). The marketing sector also benefits from predictive analytics, where models analyze consumer behavior to tailor marketing strategies and improve customer engagement (Monsalve *et al.*, 2023). Additionally, in manufacturing, predictive maintenance models forecast equipment failures, enabling timely interventions that reduce downtime and maintenance costs (Liao & Yao, 2021).

Several prediction modeling techniques are commonly employed in AI-based systems, each with its strengths and weaknesses. Among the most widely used techniques are regression analysis, decision trees, support vector machines (SVM), and neural networks (Luo *et al.*, 2022). This statistical method is used to model the relationship between a dependent variable and one or more independent variables (Monsalve *et al.*, 2023). Linear regression, for example, predicts outcomes based on a linear relationship, while logistic regression is used for binary classification tasks (Naz *et al.*, 2022). Regression models are favored for its interpretability and ease of implementation. In addition, decision trees are a non-parametric method that splits data into subsets based on feature values, creating a tree-like model of decisions (Alomar, 2022). It is intuitive and easy to visualize, making them popular for both classification and regression tasks. However, it can be prone to overfitting if not properly pruned. Moreover, SVM is a powerful classification technique that finds the optimal hyperplane to separate different classes in the feature space (Wang *et al.*, 2020). SVMs are particularly effective in high-dimensional spaces and are robust against overfitting, especially in cases where the number of dimensions exceeds the number of samples. Furthermore, NN is inspired by the human brain, neural networks consist of interconnected nodes (neurons) that process data in layers. It are particularly effective for complex tasks such as image and speech recognition (Belhadi *et al.*, 2022). Deep learning, a subset of neural networks with multiple hidden layers, has gained prominence due to its ability to learn hierarchical representations of data, leading to state-of-the-art performance in various applications. Each of these techniques has its unique advantages and is chosen based on the specific requirements of the prediction task, the nature of the data, and the desired interpretability of the model. As AI-based prediction models continue to evolve, the integration of metadata is becoming increasingly important to enhance its explainability and interoperability, ensuring that these powerful tools can be effectively utilized across diverse applications.

2.2. Explainability in AI

Explainability in artificial intelligence (AI) refers to the degree to which an AI system's internal mechanisms and decision-making processes can be understood by humans (Mikalef *et al.*, 2021; Sarker, 2022). It encompasses the ability to provide clear and comprehensible justifications for the predictions or actions taken by AI models. This characteristic is crucial in various applications, particularly in high-stakes domains such as healthcare, finance, and criminal justice, where decisions can significantly impact individuals' lives (Amellal *et al.*, 2024; Mohsen, 2023). For instance, in healthcare, explainable AI can help clinicians understand the rationale behind a model's prediction regarding patient diagnoses or treatment recommendations, thereby fostering trust and facilitating informed decision-making (Wang, 2021). The importance of explainability extends beyond mere transparency; it is also essential for regulatory compliance and ethical considerations. Many industries are subject to regulations that require organizations to provide explanations for automated decisions, especially when it affect individuals' rights (Duc & Nananukul, 2020). Furthermore, explainability can enhance user acceptance of AI systems by allowing stakeholders to challenge or validate the outcomes produced by these models, thereby promoting accountability and reducing biases (Liao & Yao, 2021).

2.2.1. Challenges associated with achieving explainability

Despite its significance, achieving explainability in AI systems presents several challenges. One primary issue is the complexity of modern AI algorithms, particularly deep learning models, which often operate as "black boxes" (Alam *et al.*, 2023). These models can achieve high levels of accuracy but at the cost of interpretability, making it difficult for users to understand how specific inputs lead to particular outputs. This opacity can lead to skepticism and reluctance to adopt AI technologies, especially in critical applications where understanding the rationale behind decisions is paramount (Mikalef *et al.*, 2021; Sarker, 2022). Another challenge is the lack of standardized definitions and metrics for explainability. The terminology surrounding explainability, interpretability, and transparency is often used interchangeably, leading to confusion and inconsistency in research and practice (Lin *et al.*, 2022; Lipton, 2018). Additionally, the trade-off between model performance and explainability complicates the development of AI systems. While simpler models may be more interpretable, it may not perform as well as more complex counterparts, creating a dilemma for practitioners.

2.3. Interoperability of AI systems

Interoperability in the context of AI systems refers to the ability of different AI applications, platforms, and components to communicate, exchange, and use information effectively, regardless of its underlying technologies or architectures (Cica *et al.*, 2020). This capability is essential for enabling seamless integration of AI solutions across disparate systems, allowing organizations to leverage diverse data sources and tools to enhance decision-making processes and operational efficiencies. The significance of interoperability cannot be overstated, especially as organizations increasingly adopt AI technologies to solve complex problems. Interoperable systems can facilitate data sharing and collaboration among stakeholders, leading to more comprehensive and informed insights (Monsalve *et al.*, 2023). In healthcare, for example, interoperability allows various systems—such as electronic health records, diagnostic tools, and treatment management platforms—to work together, improving patient care and outcomes (Guan *et al.*, 2022). Similarly, in manufacturing, interoperable AI systems can optimize supply chain management by integrating data from different sources, leading to better resource allocation and reduced operational costs (Kudama *et al.*, 2021).

2.3.1. Challenges faced by AI systems regarding interoperability

Despite its importance, achieving interoperability in AI systems presents several challenges. One primary issue is the lack of standardized protocols and data formats across different platforms. Many AI solutions are built using proprietary technologies, which can create silos of information that are difficult to integrate (Cica *et al.*, 2020). This fragmentation not only hampers data sharing but also complicates the development of cohesive AI strategies across organizations. Another challenge is the diversity of data types and structures used in AI applications. Different systems may utilize varying data schemas, making it difficult to align and integrate datasets effectively (Monsalve *et al.*, 2023). Moreover, organizations may face difficulties in reconciling disparate data quality standards, which can lead to inconsistencies and inaccuracies in AI predictions. Additionally, security and privacy concerns pose significant barriers to interoperability. Sharing sensitive data across systems can raise ethical issues and compliance challenges, particularly in regulated sectors such as healthcare and finance (Xuan *et al.*, 2024). As organizations strive to balance the need for interoperability with the imperative to protect user data, it must navigate complex regulatory landscapes that vary by region and industry.

2.4. Metadata as a catalyst for explainability and interoperability

Metadata serves as a crucial element in enhancing both explainability and interoperability of AI systems. Effective metadata usage can facilitate better understanding and integration of AI models across diverse applications. A notable case study is the use of metadata in the healthcare domain, specifically in predictive analytics for patient outcomes. The use of standardized metadata schemas in electronic health records (EHRs) has allowed for improved data sharing between hospitals and research institutions, leading to more accurate predictive models for patient care (Dumitrascu *et al.*, 2020; Mohsen, 2023). By providing clear definitions and context for clinical data, metadata has enabled healthcare providers to interpret AI model predictions more effectively, fostering trust and acceptance among clinicians. Another example can be found in the financial sector, where metadata has been instrumental in creating interoperable systems for fraud detection. By utilizing a shared metadata framework, banks and financial institutions can integrate data from various sources—such as transaction records, customer profiles, and external databases—enhancing the performance of AI models in identifying fraudulent activities (Tiyasha *et al.*, 2020; Guan *et al.*, 2022). This collaborative approach not only improves model accuracy but also demonstrates the value of metadata in achieving interoperability across different entities.

To maximize the benefits of metadata in AI systems, it is essential to establish standards and best practices for metadata management. One widely recognized framework is the

Dublin Core Metadata Initiative (DCMI), which provides a set of vocabulary terms that can be used to describe a wide range of resources, including datasets used in AI applications (Toorajipour *et al.*, 2021). Adopting such standards can promote consistency and interoperability among systems, facilitating data sharing and collaboration. Additionally, organizations should implement best practices for metadata documentation, ensuring that all metadata is accurate, up-to-date, and accessible to relevant stakeholders. This includes providing clear definitions for data elements, documenting data lineage, and specifying any transformations applied to the data (Hassouna *et al.*, 2022). Regular audits of metadata practices can also help organizations identify gaps and areas for improvement, fostering a culture of continuous enhancement in metadata management. In summary, effective metadata management plays a pivotal role in enhancing both the explainability and interoperability of AI-based prediction models. By establishing standardized metadata practices and fostering collaboration across systems, organizations can leverage the full potential of AI technologies while ensuring transparency and accountability in its applications.

3. METHODOLOGY

3.1. Research Design

This study employs a systematic review approach to evaluate the role of metadata in enhancing the explainability and interoperability of AI-based prediction models. A systematic review is a structured and comprehensive method of synthesizing existing literature, aimed at minimizing bias and providing a reliable overview of a specific research question. The systematic review process involves several key stages, including defining the research question, What role does metadata play in promoting the explainability and interoperability of AI-based prediction models? Establishing inclusion and exclusion criteria, conducting a thorough literature search, and synthesizing the findings from selected studies. The systematic review approach is particularly suitable for this research as it allows for the aggregation of diverse studies related to explainable AI (XAI) and metadata, facilitating a deeper understanding of how these elements interact within various applications. By systematically analyzing the literature, this review aims to identify trends, gaps, and best practices in the use of metadata to improve AI model interpretability and interoperability.

3.2. Search strategy

3.2.1. Databases and keywords utilized for literature identification

The literature search was conducted across several academic databases, including Scopus, Web of Science, IEEE Xplore, and PubMed. These databases were selected for its comprehensive coverage of computer science, engineering, and health-related literature, which are relevant to the study of AI and metadata. The search was limited to publications from January 2018 to September 2024 to ensure the inclusion of the most recent and relevant studies. The search strategy involved the use of specific keywords and phrases to capture a wide range of literature related to the research topic. The primary keywords included "explainable artificial intelligence," "metadata," "interoperability," "AI prediction models," and "model interpretability." Boolean operators (AND, OR) were employed to combine these keywords effectively, allowing for a more targeted search that encompassed various aspects of the research question.

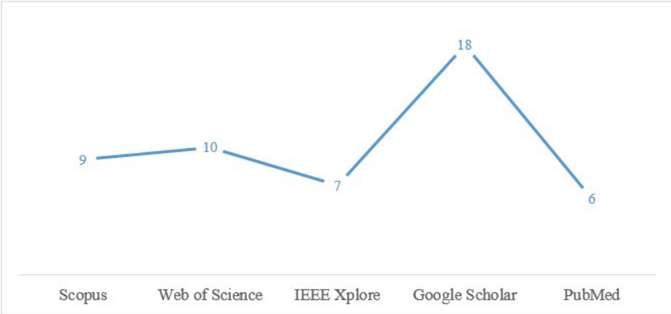

Figure 1. Sample Selection Based on Research Databases.

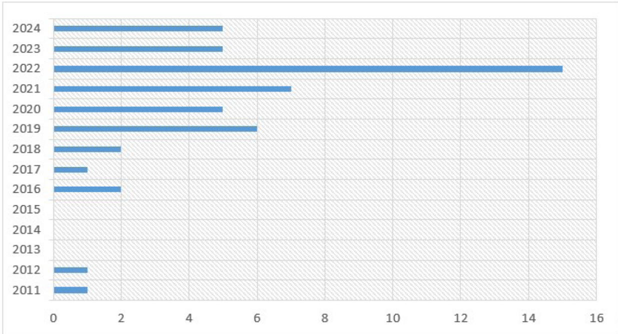

Figure 2. Distribution of Studies over Time.

3.2.2. Criteria for inclusion and exclusion of studies

Inclusion and exclusion criteria were established to ensure that only relevant studies were considered for the review. The inclusion criteria were as follows in Table 1.

Table 1. Criteria for inclusion and exclusion

Inclusion Criteria	Exclusion Criteria
Studies must focus on explainable AI, metadata, or interoperability in the context of AI-based prediction models.	Studies that did not address the core themes of explainability, metadata, or interoperability in AI were excluded.
Only articles published between January 2018 and October 2022 were included to capture recent developments in the field.	Articles published in languages other than English were excluded to maintain consistency in the review process.
Only peer-reviewed articles, conference papers, and systematic reviews were considered to ensure the quality and credibility of the literature.	Any duplicate studies identified across the databases were removed to avoid redundancy in the analysis.

By adhering to these criteria, the systematic review aimed to compile a robust and relevant body of literature that would provide insights into the role of metadata in enhancing the explainability and interoperability of AI-based prediction models.

3.3. Data extraction and synthesis

3.3.1. Framework for extracting relevant data from selected studies

The data extraction process in this systematic review is guided by a structured framework called PRISMA designed to capture essential information from each selected study. This framework is crucial for ensuring consistency and comprehensiveness in the data collected, which ultimately supports the synthesis and analysis of findings. The extraction process involves the use of a standardized data extraction form that includes key fields relevant to the research question. This structured approach allows for the systematic organization of data, facilitating easier comparison and analysis across studies. The extraction process is typically conducted by multiple reviewers to enhance reliability, with discrepancies resolved through discussion or consensus.

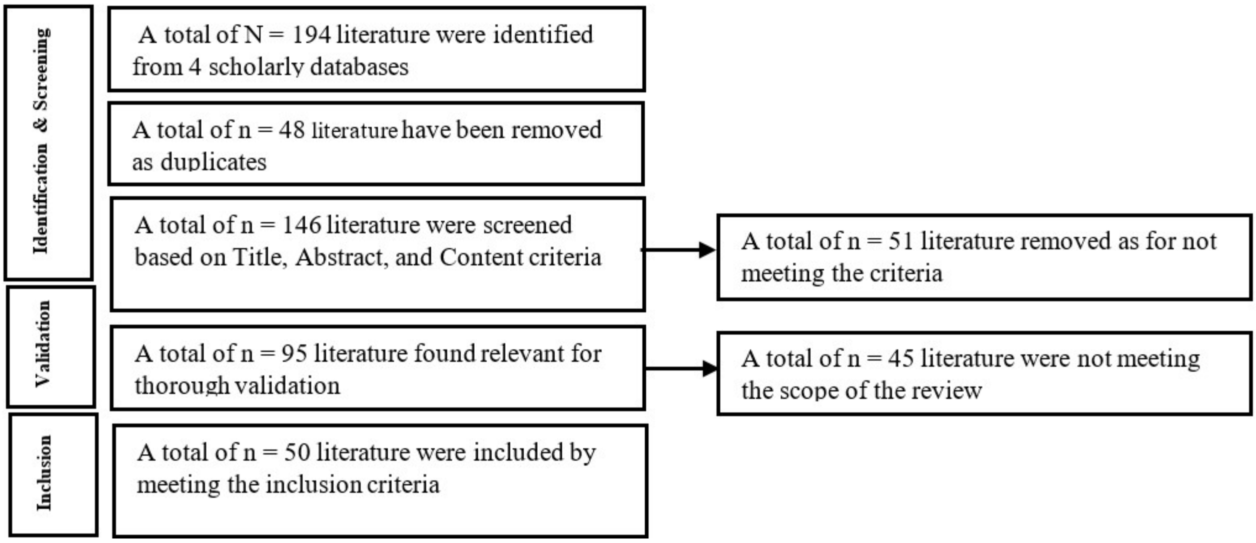

Figure 3. Literature samples diagram of the study

3.3.2. Methods for synthesizing and analyzing findings

Once the relevant data has been extracted, the next step involves synthesizing and analyzing the findings from the selected studies. For studies that provide rich descriptive data, a qualitative synthesis method, such as thematic analysis, may be employed. This involves identifying common themes and patterns across the studies, particularly regarding the role of metadata in enhancing explainability and interoperability. Thematic analysis allows for a nuanced understanding of how different studies approach the use of metadata and its impact on AI systems (Braun & Clarke, 2006). By employing these methods for data extraction and synthesis, the systematic review aims to provide a thorough and coherent understanding of the role of metadata in enhancing the explainability and interoperability of AI-based prediction models. This structured approach not only ensures the reliability of the findings but also contributes to the broader discourse on effective practices in AI research and application.

4. RESULTS AND DISCUSSION

4.1. Key findings

The systematic review revealed several critical insights into the role of metadata in enhancing both the explainability and interoperability of AI-based prediction models. One of the primary findings is that metadata significantly contributes to the interpretability of AI models by providing contextual information about the data used in model training and evaluation. Studies indicated that well-structured metadata allows users to understand the features and variables influencing model predictions, thereby increasing trust in AI systems (Cica *et al.*, 2020). For instance, descriptive metadata that includes definitions of input features and its relationships to outcomes can help stakeholders grasp how decisions are made, which is particularly important in high-stakes environments like healthcare and finance (Mohsen, 2023). Moreover, the review highlighted that interoperability is greatly enhanced through the use of standardized metadata frameworks. By adopting common metadata standards, different AI systems can more easily share and integrate data, facilitating collaborative efforts across organizations (Monsalve *et al.*, 2023). This interoperability is crucial for creating comprehensive AI solutions that leverage diverse datasets, ultimately leading to improved model performance and more informed decision-making.

4.2. Description of different types of metadata

Metadata is defined as data that provides information about other data, serving as a critical component in data management and utilization (Cotrufo *et al.*, 2019). There are several types of metadata, each serving distinct purposes.

i. Descriptive Metadata: This type of metadata provides information about the content and context of data, including titles, authors, keywords, and summaries. Descriptive metadata helps users discover and understand the data, facilitating effective data retrieval and usage (Deb & Gupta, 2023).

ii. Structural Metadata: Structural metadata describes the organization and relationships between different data elements. It includes information about how data is structured, such as the format, schema, and data types. This type of metadata is essential for understanding how to navigate and manipulate datasets (Dokeroglu *et al*., 2019).

iii. Administrative Metadata: Administrative metadata provides information necessary for managing and maintaining data, including details about data ownership, access rights, and data provenance. This type of metadata is crucial for ensuring data integrity, security, and compliance with regulations (Arora & Singh, 2019).

4.3. Role of metadata in enhancing model interpretability

Metadata plays a vital role in enhancing the interpretability of AI-based prediction models. By providing context and additional information about the data used in modeling, metadata can help users understand the underlying assumptions and limitations of the models (Deb & Gupta, 2023). For example, descriptive metadata can clarify the meaning of input features, enabling users to grasp how these features influence model predictions. Moreover, structural metadata can facilitate the integration of different datasets, promoting interoperability among AI systems. When models are built on well-documented metadata, it becomes easier to share and reuse data across various applications, enhancing collaboration and innovation (Cica *et al*., 2020). Administrative metadata further supports interpretability by ensuring that users are aware of the data's lineage and any potential biases or ethical considerations associated with its use (Dabbas & Friedrich, 2022). In summary, effective metadata management is essential for improving the explainability and interoperability of AI-based prediction models, ultimately leading to more trustworthy and user-friendly AI systems.

4.4. Comparative analysis

The analysis also included a comparative evaluation of various prediction modeling techniques concerning its metadata requirements. Different modeling techniques exhibit varying levels of complexity and interpretability, which directly influences its metadata needs (Table 2 and Table 3). Comparative Analysis of Modeling Techniques: Regression Models, Decision Trees, Support Vector Machines, and Neural Networks.

Table 2. Different modeling techniques

Prediction Model	Description	Source
Regression Models	These models, particularly linear regression, are generally more interpretable and require less complex metadata	(Monsalve *et al*., 2023; Mohsen, 2023)
Decision Trees	Decision trees are inherently interpretable due to its visual structure, but it still benefit from comprehensive metadata	(Luo *et al*., 2022)
Support Vector Machines (SVM)	SVMs, while powerful, are less interpretable than regression models and decision trees	(Monsalve *et al*., 2023)
Neural Networks	Deep learning models, particularly neural networks, present the greatest challenge in terms of explainability and metadata requirements	(Duc & Nananukul, 2020; Šustrová, 2016)

In the realm of predictive analytics and machine learning, various modeling techniques serve distinct purposes and come with unique advantages and disadvantages. This analysis will compare four prominent modeling techniques: Regression Models, Decision Trees, Support Vector Machines (SVM), and Neural Networks. Based on Table 3, the choice of modeling technique depends on the specific requirements of the task at hand. Regression models are suitable for simple, linear relationships and small datasets. Decision trees offer interpretability and handle non-linearity well but risk overfitting (Fan & Shen, 2022; Monsalve *et al*., 2023; Šustrová, 2016). Support Vector Machines shine in high-dimensional spaces but come with complexity and computational demands (Wang *et al*., 2020). Neural networks excel in capturing complex patterns in large datasets but sacrifice interpretability (Fan & Shen, 2022; Modesti & Borsato, 2022; Zhang & Duan, 2022). Ultimately, the selection of a modeling technique should be guided by factors such as data characteristics, the complexity of the task, and the need for interpretability. Each modeling technique serves distinct purposes and is suited to different types of data and problem complexities. Regression models are best for straightforward relationships, while decision trees offer intuitive interpretations with flexibility.

Table 3. Critical review analysis on the role of metadata in promoting explainability and interoperability of ai-based models

Criteria	Regression Models	Decision Trees	Support Vector Machines	Neural Networks	Source
Overview	Regression models are statistical methods used for predicting the value of a dependent variable based on one or more independent variables. The most common form is linear regression, which assumes a linear relationship between the variables.	Decision trees model decisions and their possible consequences as a tree-like graph of decisions. They are intuitive and easy to visualize.	SVM is a supervised learning algorithm used for classification and regression tasks. It works by finding a hyperplane that best separates data points of different classes.	Neural networks are computational models inspired by the human brain, consisting of layers of interconnected nodes (neurons). They are capable of capturing complex patterns in data.	(Abiodun *et al.*, 2018; Amellal *et al.*, 2024; Baryannis *et al.*, 2019; Buczak & Guven, 2016; Dokeroglu *et al.*, 2019; Helo & Hao, 2022; Liao & Yao, 2021; Xu *et al.*, 2021)
Advantages	-Simplicity: Easy to understand and interpret. -Performance: Performs well with linear relationships and smaller datasets. -Speed: Generally computationally efficient, allowing for quick training and predictions.	- Interpretability: Provides clear visual representation of decisions, making it easy to understand. -Non-linearity: Can handle non-linear relationships without requiring transformation of the data. -Feature Importance: Identifies the most important features in the dataset	-Effectiveness in High Dimensions: Performs well in high-dimensional spaces, making it suitable for complex datasets. -Robustness: Effective in cases where the number of dimensions exceeds the number of samples. -Kernel Trick: The ability to use different kernels allows for flexibility in fitting the data.	-Flexibility: Can model complex non-linear relationships and interactions between features. -Scalability: Suitable for large datasets and can be scaled up with additional layers (deep learning). -Performance: Often yields high accuracy in tasks like image and speech recognition.	(Deb & Gupta, 2023; Ding *et al.*, 2011; Elsken *et al.*, 2019; Ghodousian, 2018)
Disadvantages	-Assumptions: Assumes a linear relationship; may underperform with non-linear data. -Outliers: Sensitive to outliers, which can skew results significantly. -Limited Complexity: Not suitable for capturing intricate patterns within large datasets.	-Overfitting: Prone to overfitting, especially with complex trees. -Instability: Small changes in the data can lead to very different trees. -Bias: Can be biased towards features with more levels (categorical variables).	-Complexity: More complex than regression and decision trees, making interpretation challenging. -Computationally Intensive: Training time can be high on large datasets, especially with non-linear kernels. -Parameter Tuning: Requires careful tuning of parameters for optimal performance.	-Interpretability: Often considered a “black box,” making it difficult to interpret results. -Data Hungry: Requires large amounts of data for effective training. -Training Time: Can be computationally expensive and time-consuming to train.	(Abiodun *et al.*, 2018; Amellal *et al.*, 2024; Baryannis *et al.*, 2019; Buczak & Guven, 2016; Dokeroglu *et al.*, 2019; Helo & Hao, 2022; Liao & Yao, 2021; Xu *et al.*, 2021)

Criteria	Regression Models	Decision Trees	Support Vector Machines	Neural Networks	Source
Types	-Linear Regression: Assumes a straight-line relationship. -Multiple Regression: Involves multiple independent variables. -Polynomial Regression: Captures non-linear relationships by using polynomial equations.	- Classification Trees: Used for categorical outcomes. -Regression Trees: Used for continuous outcomes.	Kernel Trick: SVMs can use kernel functions (linear, polynomial, RBF) to transform data into higher dimensions, allowing for non-linear separation.	-Convolutional Neural Networks (CNNs): Specialized for image processing. -Recurrent Neural Networks (RNNs): Designed for sequential data, such as time series or text.	(M. K. Alomar *et al.*, 2020; Brdesee & Arabia, 2021; Cotrufo *et al.*, 2019; Mirjalili *et al.*, 2017; Monsalve *et al.*, 2023; Wei, 2022; Zhang & Duan, 2022)
Mathematical Foundation	The linear regression model can be expressed as: $y = \beta0 + \beta1*x1 + \beta2*x2 + ... + \betan*xn + \varepsilon$ Where: y is the dependent variable. β0 is the intercept. `β1, β2, … βn` are the coefficients for independent variables `x1, x2, …, xn`. `ε` is the error term.	Decision trees use algorithms such as CART (Classification and Regression Trees) to split nodes based on metrics like Gini impurity or entropy for classification, and mean squared error for regression.	The goal of SVM is to maximize the margin between classes, represented mathematically as: minimize: $\|w\|^2$ subject to: $y(i) (w \cdot x(i) + b) \geq 1$ for all i Where: `w` is the weight vector. `b` is the bias. `y(i)` is the class label.	A simple neural network can be described as: $y = f(W * x + b)$. Where: `W` is the weight matrix. `x` is the input vector. `b` is the bias vector. `f` is the activation function (e.g., sigmoid, ReLU). Training: Neural networks are trained using backpropagation and optimization techniques like gradient descent.	(Brdesee & Arabia, 2021; Cotrufo *et al.*, 2019; Kusiak *et al.*, 2012; Luo *et al.*, 2022; G. Wang *et al.*, 2020)
Applications	-Economic forecasting, risk assessment, and any scenario with a clear relationship between variables.	-Customer segmentation, loan approval processes, and medical diagnosis.	-Text classification, image recognition, and bioinformatics.	-Natural language processing, image and speech recognition, and game playing (e.g., reinforcement learning). Architecture: Input Layer: Receives the input features; Hidden Layers: Perform computations and feature extraction; and Output Layer: Produces the final prediction.	(M. K. Alomar *et al.*, 2020; Belhadi *et al.*, 2022; Modesti & Borsato, 2022; Monsalve *et al.*, 2023; Šustrová, 2016; Zhang & Duan, 2022)
Interpretability	High	High	Medium	Low	(M. K. Alomar *et al.*, 2020; Buczak & Guven, 2016; Cotrufo *et al.*, 2019; Elsken *et al.*, 2019)

Criteria	**Regression Models**	**Decision Trees**	**Support Vector Machines**	**Neural Networks**	**Source**
Handling Non-linearity	Limited (unless transformed)	Strong	Strong (with Kernel trick)	Very Strong	(Belhadi *et al.*, 2022; Cotrufo *et al.*, 2019; Du *et al.*, 2019; Kusiak *et al.*, 2012)
Overfitting Risk	Moderate	High (especially with deep trees)	Moderate	High (especially with many layers)	(Alam *et al.*, 2023; M. K. Alomar *et al.*, 2020; Belhadi *et al.*, 2022; Brdesee & Arabia, 2021; Fan & Shen, 2022; Luo *et al.*, 2022; Monsalve *et al.*, 2023; Šustrová, 2016; G. Wang *et al.*, 2020)
Data Requirements	Low to Medium	Medium	Medium to High	High	(Banu *et al.*, 2022; Belhadi *et al.*, 2022; Cotrufo *et al.*, 2019)
Computational Cost	Low to Medium	Low to Medium	High	High	(M. K. Alomar *et al.*, 2020; Brdesee & Arabia, 2021; Lokare & Jadhav, 2024)
Best Use Cases	Predictive modeling	Decision support systems		Complex classification tasks	Complex pattern recognition

Support Vector Machines excel in high-dimensional spaces, and neural networks are unrivaled in their capability to model complex, non-linear relationships in large datasets (Monsalve *et al.*, 2023; Wang *et al.*, 2020). The selection of the appropriate model should consider the specific context and requirements of the problem, as well as the data available. By leveraging the strengths of these techniques, practitioners can build robust predictive models that yield valuable insights.

These models, particularly linear regression, are generally more interpretable and require less complex metadata (Monsalve *et al.*, 2023). The essential metadata includes variable definitions and relationships, which are straightforward to document. Studies showed that when metadata is clear and accessible, it enhances the understanding of regression outputs, making it easier for users to interpret the results (Mohsen, 2023). Metadata that describes the criteria used for splits and the significance of each feature can enhance user understanding of the model's decision-making process (Luo *et al.*, 2022). The review found that providing detailed metadata alongside decision trees significantly improves stakeholder confidence in the model's predictions. The complexity of the model necessitates more extensive metadata to explain the kernel functions and hyperparameters used. The review indicated that without adequate metadata, users may struggle to understand how SVMs arrive at its classifications, which can hinder its adoption in critical applications (Banu *et al.*, 2022). The intricate architecture of these models requires detailed metadata that documents the layers, activation functions, and training processes. The review highlighted that while neural networks can achieve high accuracy, its lack of transparency can be mitigated through robust metadata practices that clarify how inputs are transformed into outputs (Belhadi *et al.*, 2022). The findings underscore the importance of metadata in enhancing both the explainability and interoperability of AI-based prediction models. By tailoring metadata practices to the specific requirements of different modeling techniques, organizations can improve user understanding and facilitate better integration of AI systems across various applications. This approach not only fosters trust in AI technologies but also promotes collaborative efforts that leverage diverse data sources for more effective decision-making.

4.5. Practical implications

The findings from this systematic review emphasize the critical role of metadata in improving the explainability and interoperability of AI-based prediction models. Practitioners across various sectors can implement several strategies to leverage metadata effectively, thereby maximizing the benefits of AI technologies. Practitioners should prioritize the adoption of standardized metadata frameworks, such as the Dublin Core or Data Catalog Vocabulary (DCAT). Standardization facilitates interoperability by ensuring that different systems can understand and utilize metadata consistently (Amellal *et al.*, 2024). By adhering to established standards, organizations can enhance data sharing and collaboration, leading to improved model integration across platforms. It is crucial for organizations to invest in thorough metadata documentation practices. This includes clearly defining key variables, data sources, and data processing methods. Comprehensive metadata documentation not only improves model interpretability but also aids in regulatory compliance, particularly in sectors such as healthcare and finance where transparency is paramount (Li *et al.*, 2021; Song *et al.*, 2024). Practitioners should ensure that metadata is updated regularly to reflect any changes in data or modeling approaches. Practitioners should leverage descriptive metadata to provide context for model inputs and outputs. By including detailed descriptions of features, its significance, and relationships to outcomes, organizations can enhance user understanding of model predictions (Mohsen, 2023). This practice is particularly important in high-stakes environments where decision-makers rely on AI insights to guide critical actions. To foster a culture of data literacy, organizations should implement training programs that educate stakeholders about the importance of metadata in AI systems. Training should focus on how to interpret metadata and leverage it to understand model outputs better. This knowledge can empower users to ask critical questions about the AI systems it interact with, promoting accountability and informed decision-making (Cica *et al.*, 2020). Effective metadata practices often require collaboration between data scientists and domain experts. Practitioners should encourage cross-disciplinary teams to work together in defining metadata elements that reflect both technical requirements and domain-specific knowledge. This collaboration can lead to the creation of more relevant and usable metadata that enhances both explainability and interoperability (Monsalve *et al.*, 2023).

Furthermore, organizations should leverage metadata not only for initial model development but also for ongoing monitoring and improvement. By analyzing metadata related to model performance, practitioners can identify areas where explainability can be enhanced or where interoperability issues arise due to changes in data sources or structures. This continuous improvement approach supports adaptive learning in AI systems, ensuring it remain effective and trustworthy over time (Elsken *et al.*, 2019). Finally, establishing governance policies for metadata management is essential. Organizations should define roles and responsibilities for metadata creation, maintenance, and usage. Governance frameworks can help ensure data quality, compliance with regulatory requirements, and alignment with organizational goals. This structured approach to metadata management can enhance overall data stewardship within the organization (Mohsen, 2023). By implementing these recommendations, practitioners can effectively leverage metadata to enhance the explainability and interoperability of AI-based prediction models. This not only improves stakeholder trust and engagement but also facilitates more informed decision-making and collaboration across various domains.

4.6. Limitations and future research directions

While this systematic review has provided valuable insights into the role of metadata in enhancing the explainability and interoperability of AI-based prediction models, several gaps in the existing literature warrant further exploration. One significant gap is the lack of empirical studies that rigorously test the impact of specific metadata practices on model performance and user understanding. Most studies reviewed were theoretical or descriptive in nature, suggesting a need for experimental research that quantifies the effects of various metadata strategies on explainability and interoperability (Monsalve *et al.*, 2023). Another identified gap is the insufficient focus on the challenges and best practices in metadata management across different industries. While some sectors, such as healthcare, have made strides in metadata standardization, others lag behind. Research is needed to explore industry-specific metadata frameworks and its effectiveness in promoting interoperability among disparate systems (Song *et al.*, 2024). Moreover, there is a limited understanding of how emerging technologies like blockchain and the Internet of Things (IoT) can influence metadata practices and enhance interoperability. As these technologies become more prevalent, it is vital to investigate how it can be integrated with AI systems to facilitate more robust metadata management, thereby improving overall system interoperability (Cica *et al.*, 2020). Lastly, the review highlighted a need for more inclusive studies that consider diverse stakeholder perspectives on metadata usage. Current literature often focuses on technical aspects without adequately addressing the viewpoints of end-users, decision-makers, and other stakeholders affected by AI systems. Research that incorporates these perspectives can provide a more holistic understanding of how metadata influences user engagement and trust in AI technologies (Mohsen, 2023).

Future research should focus on conducting empirical studies that evaluate the effectiveness of specific metadata practices in enhancing model explainability and interoperability. These studies could employ experimental designs to assess how different metadata structures impact user understanding and decision-making in real-world applications. Research should explore the development and implementation of industry-specific metadata frameworks that cater to the unique needs of various sectors. This could involve case studies or pilot projects that assess the effectiveness of these frameworks in promoting interoperability and compliance with regulatory standards. Investigating the role of emerging technologies, such as blockchain and IoT, in enhancing metadata management and interoperability is a critical area for future research. Studies could explore how these technologies can be leveraged to create more transparent and secure metadata practices, fostering greater trust in AI systems. Future research should prioritize a stakeholder-centric approach that includes diverse perspectives on metadata usage. Qualitative studies involving interviews and focus groups with end-users, data scientists, and decision-makers can provide valuable insights into how metadata is perceived and utilized across different contexts. Conducting longitudinal studies to track the impact of metadata practices over time can offer insights into how sustained efforts in metadata management influence model performance, user trust, and system interoperability. This type of research can help organizations understand the long-term benefits of investing in robust metadata practices. While this review has contributed to the understanding of metadata's role in AI-based prediction models, addressing the identified limitations and pursuing the suggested research directions will be crucial for advancing the field. Continued exploration of these areas will not only enhance the academic discourse but also provide practical guidance for practitioners in effectively leveraging metadata for improved AI outcomes.

5. CONCLUSIONS

In summary, this systematic review has underscored the pivotal role of metadata in enhancing the explainability and interoperability of AI-based prediction models. As artificial intelligence continues to permeate various sectors, including healthcare, finance, and transportation, the need for transparent and interpretable AI systems becomes increasingly critical. Metadata serves as a foundational element that not only provides context to the data used in AI models but also facilitates a clearer understanding of how these models operate and make decisions. By effectively documenting and managing metadata, organizations can significantly improve user trust and engagement with AI technologies, ultimately leading to better decision-making outcomes. Moreover, the findings highlight that advancing metadata practices is essential for overcoming the challenges associated with the black-box nature of many AI models. As AI systems grow in complexity, the interpretability of its outputs often diminishes, creating barriers to its adoption in sensitive applications where understanding the rationale behind decisions is crucial. By implementing standardized metadata frameworks and investing in comprehensive documentation practices, organizations can enhance the transparency of its AI systems, making it easier for stakeholders to comprehend and trust the predictions generated. The importance of metadata in AI technologies cannot be overstated. As the field of artificial intelligence continues to evolve, ongoing research and practical efforts to improve metadata management will be vital. This will not only foster greater explainability and interoperability but also ensure that AI systems are developed and deployed responsibly, with a focus on ethical considerations and user empowerment. Future research should aim to fill the existing gaps in the literature, particularly regarding empirical studies and industry-specific metadata practices, to further advance the understanding and application of metadata in AI-based prediction models.

REFERENCES

Abdulganiyu, J., Musa, M. N., Matayo, V. A., Saidu, A. A., & Ahmed, A. A. (2023). Integrating Business Intelligence and Small and Medium Enterprises for Shifting Africa from Consumption to a Production and Industrialised Economy. Spectrum International *Journal of Multidisciplinary Research, 1*(2), 1–9.

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon, 4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Alam, M., Haque, A., Khan, A. I., Kasim, S., Pasha, A. A., Zafar, A., Irshad, K., Chaudhary, A. A., & Azim, R. (2023). Metasurface-Based Solar Absorption Prediction System Using Artificial Intelligence. *Journal of Mathematics, 2023*(9489270), 1–18. https://doi.org/https://doi.org/10.1155/2023/9489270

Alomar, M. A. (2022). Performance Optimization of Industrial Supply Chain Using Artificial Intelligence. *Computational Intelligence and Neuroscience, 2022*(9306265), 1–10. https://doi.org/https://doi.org/10.1155/2022/9306265

Alomar, M. K., Hameed, M. M., Al-ansari, N., & Alsaadi, M. A. (2020). Data-Driven Model for the Prediction of Total Dissolved Gas: Robust Artificial Intelligence Approach. *Advances in Civil Engineering, 2020*(6618842), 1–120. https://doi.org/https://doi.org/10.1155/2020/6618842

Amellal, I., Amellal, A., Seghiouer, H., & Ech-charrat, M. R. (2024). An integrated approach for modern supply chain management: Utilizing advanced machine learning models for sentiment analysis, demand forecasting, and probabilistic price prediction. *Decision Science Letters, 13*(2024), 237–248. https://doi.org/10.5267/dsl.2023.9.003

Arora, S., & Singh, S. (2019). Butterfly optimization algorithm: a novel approach for global optimization. *Soft Computing, 23*(3), 715–734. https://doi.org/10.1007/s00500-018-3102-4

Banu, J. F., Neelakandan, S., Geetha, B. T., Selvalakshmi, V., Umadevi, A., & Martinson, E. O. (2022). Artificial Intelligence Based Customer Churn Prediction Model for Business Markets. *Computational Intelligence and Neuroscience, 2022*(1703696), 1–14. https://doi.org/https://doi.org/10.1155/2022/1703696

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research, 57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2022). Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. *International Journal of Production Research, 60*(14), 4487–4507. https://doi.org/10.1080/00207543.2021.1950935

Brdesee, H. S., Alsaggaf, W., Aljohani, N., & Hassan, S. U. (2022). Predictive model using a machine learning approach for enhancing the retention rate of students at-risk. *International Journal on Semantic Web and Information Systems (IJSWIS), 18*(1), 1-21. https://doi.org/10.4018/IJSWIS.299859

Buczak, A. L., & Guven, E. (2016). A Survey of Data Mining and Machine Learning Methods for Cyber Security Intrusion Detection. *IEEE Communications Surveys and Tutorials, 18*(2), 1153–1176. https://doi.org/10.1109/COMST.2015.2494502

Cica, D., Sredanovic, B., & Tesic, S. (2020). Predictive modeling of turning operations under different cooling / lubricating conditions for sustainable manufacturing with machine learning techniques. *Applied Computing and Informatics, 20*(1), 162–180. https://doi.org/10.1016/j.aci.2020.02.001

Cotrufo, N., Saloux, E., Hardy, J. M., Candanedo, J. A., & Platon, R. (2019). A practical Artificial Intelligence-based approach for predictive control in commercial and. *Energy & Buildings*, 109563. https://doi.org/10.1016/j.enbuild.2019.109563

Dabbas, H., & Friedrich, B. (2022). Benchmarking machine learning algorithms by inferring transportation modes from unlabeled GPS data. *Transportation Research Procedia, 62*(Ewgt 2021), 383–392. https://doi.org/10.1016/j.trpro.2022.02.048

Deb, I., & Gupta, R. K. (2023). A genetic algorithm based heuristic optimization technique for solving balanced allocation problem involving overall shipping cost minimization with restriction to the number of serving units as well as customer hubs. *Results in Control and Optimization, 11*(June 2022), 100227. https://doi.org/10.1016/j.rico.2023.100227

Ding, S., Su, C., & Yu, J. (2011). An optimizing BP neural network algorithm based on genetic algorithm. Artificial Intelligence Review, 36(2), 153–162. https://doi.org/10.1007/s10462-011-9208-z

Dokeroglu, T., Sevinc, E., Kucukyilmaz, T., & Cosar, A. (2019). A survey on new generation metaheuristic algorithms. *Computers and Industrial Engineering, 137*(May). https://doi.org/10.1016/j.cie.2019.106040

Du, M., Luo, J., Wang, S., & Liu, S. (2019). Genetic algorithm combined with BP neural network in hospital drug inventory management system. *Neural Computing and Applications, 3.* https://doi.org/10.1007/s00521-019-04379-3

Duc, D. N., & Nananukul, N. (2020). A Hybrid Methodology Based on Machine Learning for a Supply Chain Optimization Problem. *Journal of Physics: Conference Series, 1624*(052022). https://doi.org/10.1088/1742-6596/1624/5/052022

Dumitrascu, O., Dumitrascu, M., & Dobrotă, D. (2020). Performance evaluation for a sustainable supply chain management system in the automotive industry using artificial intelligence. *Processes, 8*(11), 1–20. https://doi.org/10.3390/pr8111384

Elsken, T., Metzen, J. H., & Hutter, F. (2019). Survey on neural architecture search. *Journal of Machine Learning Research, 20*(2019), 1–21. https://doi.org/10.11834/jig.200202

Fan, J., & Shen, P. (2022). Financial Stock Investment Management Using Deep Learning Algorithm in the Internet of Things. *Computational Intelligence and Neuroscience, 2022*(4514300), 1–10. https://doi.org/https://doi.org/10.1155/2022/4514300

Ghodousian, A. (2018). An Algorithm for Solving Linear Optimization Problems Subjected to the Intersection of Two Fuzzy Relational Inequalities Defined by Frank Family of T-Norms. *International Journal in Foundations of Computer Science & Technology, 8*(3), 01–20. https://doi.org/10.5121/ijfcst.2018.8301

Guan, Y., Huang, Y., & Qin, H. (2022). Inventory Management Optimization of Green Supply Chain Using IPSO-BPNN Algorithm under the Artificial Intelligence. 2022.

Hassouna, M., El-henawy, I., & Haggag, R. (2022). A Multi-Objective Optimization for supply chain management using Artificial Intelligence (AI). *International Journal of Advanced Computer Science and Applications, 13*(8). 13(8), 140–149.

Helo, P., & Hao, Y. (2022). Artificial intelligence in operations management and supply chain management: an exploratory case study. *Production Planning and Control, 33*(16), 1573–1590. https://doi.org/10.1080/09537287.2021.1882690

Kudama, G., Dangia, M., Wana, H., & Tadese, B. (2021). Artificial Intelligence in Agriculture Will digital solution transform Sub-Sahara African agriculture? *Artificial Intelligence in Agriculture, 5*, 292–300. https://doi.org/10.1016/j.aiia.2021.12.001

Kusiak, J., Szeliga, D., & Sztangret, Ł. (2012). Modelling techniques for optimizing metal forming processes. In *Microstructure Evolution in Metal Forming Processes.* Woodhead Publishing Limited. https://doi.org/10.1533/9780857096340.1.35

Li, X., Ren, S., & Gu, F. (2021). Medical Internet of Things to Realize Elderly Stroke Prevention and Nursing Management. *Journal of Healthcare Engineering, 2021*(9989602), 1–12.

Liao, M., & Yao, Y. (2021). Applications of artificial intelligence-based modeling for bioenergy systems: A review. *GCB-Bioenergy, 2021*(January), 774–802. https://doi.org/https://doi.org/10.1111/gcbb.12816

Lin, H., Lin, J., & Wang, F. (2022). An innovative machine learning model for supply chain management. *Journal of Innovation & Knowledge, 7*(4), 100276. https://doi.org/10.1016/j.jik.2022.100276

Lokare, V. T., & Jadhav, P. M. (2024). An AI-based learning style prediction model for personalized and effective learning. *Thinking Skills and Creativity, 51*(November 2023), 101421. https://doi.org/10.1016/j.tsc.2023.101421

Luo, S., Xing, M., & Zhao, J. (2022). Construction of Artificial

Intelligence Application Model for Supply Chain Financial Risk Assessment. *Scientific Programming, 2022*(4194576), 1–8. https://doi.org/https://doi.org/10.1155/2022/4194576

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Olsen, S., Yngvar, H., Gupta, M., & Niehaves, B. (2021). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly*, June. https://doi.org/10.1016/j.giq.2021.101596

Mirjalili, S., Gandomi, A. H., Mirjalili, S. Z., Saremi, S., Faris, H., & Mirjalili, S. M. (2017). Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. *Advances in Engineering Software, 114*, 163–191. https://doi.org/10.1016/j.advengsoft.2017.07.002

Modesti, P., Ribeiro, J. K., & Borsato, M. (2024). Artificial intelligence-based method for forecasting flowtime in job shops. *VINE Journal of Information and Knowledge Management Systems, 54*(2), 452-472. https://doi.org/10.1108/VJIKMS-08-2021-0146

Mohsen, B. M. (2023). Developments of Digital Technologies Related to Supply Chain Management. *Procedia Computer Science, 220*, 788–795. https://doi.org/10.1016/j.procs.2023.03.105

Monsalve, M. O., Caron-Munoz, M., Galeano-vasco, L., & Medina-Sierra, M. (2023). Use of Machine Learning Models for Prediction of Organic Carbon and Nitrogen in Soil from Hyperspectral Imagery in Laboratory Manuela Ortega Monsalve , Mario Cer on-Muñoz. *Journal of Spectroscopy, 2023*(4389885), 1–8. https://doi.org/https://doi.org/10.1155/2023/4389885

Naz, F., Kumar, A., Majumdar, A., & Agrawal, R. (2022). Is artificial intelligence an enabler of supply chain resiliency post COVID-19? An exploratory state-of-the-art review for future research. *Operations Management Research, 15*(1–2), 378–398. https://doi.org/10.1007/s12063-021-00208-w

Sarker, I. H. (2022). AI - Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science, 3*(2), 1–20. https://doi.org/10.1007/s42979-022-01043-x

Song, R., Pang, F., Jiang, H., & Zhu, H. (2024). A machine learning based method for constructing group profiles of university students. *Heliyon, 10*(7), e29181. https://doi.org/10.1016/j.heliyon.2024.e29181

Šustrová, T. (2016). A Suitable Artificial Intelligence Model for Inventory Level Optimization. *Trends Economics and Management, 8527*(1), 48–55. https://doi.org/http://dx.doi.org/10.13164/trends.2016.25.48

Tiyasha, Tung, T. M., & Yaseen, Z. M. (2020). A survey on river water quality modelling using artificial intelligence models: 2000–2020. *Journal of Hydrology, 585*(October 2019), 124670. https://doi.org/10.1016/j.jhydrol.2020.124670

Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research, 122*(September 2020), 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009

Wang, G., Wei, J., & Yao, B. (2020). A Coalmine Water Inrush Prediction Model Based on Artificial Intelligence. *International Journal of Safety and Security Engineering, 10*(4), 501–508. https://doi.org/https://doi.org/10.18280/ijsse.100409 Received:

Wang, S. (2021). Artificial Intelligence Applications in the New Model of Logistics. *Scientific Programming, 2021*(5166993), 1–5. https://doi.org/https://doi.org/10.1155/2021/5166993

Wei, Y. (2022). A Machine Learning Algorithm for Supplier Credit Risk Assessment Based on Supply Chain Management. *International Transactions on Electrical Energy Systems, 2022*(4766597), 1–11. https://doi.org/https://doi.org/10.1155/2022/4766597

Xu, A., Chang, H., Xu, Y., Li, R., Li, X., & Zhao, Y. (2021). Applying artificial neural networks (ANNs) to solve solid waste-related issues: A critical review. *Waste Management, 124*, 385–402. https://doi.org/10.1016/j.wasman.2021.02.029

Xuan, P., Quoc, P., Mai, H., Hung, Q., & Pham, T. (2024). Enhancing educational evaluation through predictive student assessment modeling. *Computers and Education: Artificial Intelligence, 6*(May), 100244. https://doi.org/10.1016/j.caeai.2024.100244

Zhang, S., & Duan, C. (2022). Clustering Optimization Algorithm for Data Mining Based on. *Wireless Communications and Mobile Computing, 2022*(1304951), 1–16. https://doi.org/https://doi.org/10.1155/2022/1304951