

Review

AI in Context: Harnessing Domain Knowledge for Smarter Machine Learning

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Abstract: This article delves into the critical integration of domain knowledge into AI/ML systems across various industries, highlighting its importance in developing ethically responsible, effective, and contextually relevant solutions. Through detailed case studies from the healthcare and manufacturing sectors, we explore the challenges, strategies, and successes of this integration. We discuss the evolving role of domain experts and the emerging tools and technologies that facilitate the incorporation of human expertise into AI/ML models. The article forecasts future trends, predicting a more seamless and strategic collaboration between AI/ML and domain expertise. It emphasizes the necessity of this synergy for fostering innovation, ensuring ethical practices, and aligning technological advancements with human values and real-world complexities.

Keywords: domain expertise in AI; AI/ML ethical practices; industry-specific AI applications; predictive analytics in AI; technological innovation in AI/ML



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1. Introduction

In an epoch where artificial intelligence (AI) and machine learning (ML) inexorably redefine the frontiers of human capability and ingenuity, the infusion of domain-specific knowledge into these computational behemoths emerges not merely as an option but as an imperative [1]. This foundational chapter endeavors to delineate the profound significance of amalgamating domain expertise with AI and ML methodologies, thereby unraveling the multifaceted benefits and the intricate challenges inherent in this integration [2,3].

At the core of this discussion is the recognition that while AI and ML are excellent at pattern recognition and predictive analytics, their effectiveness is greatly enhanced when combined with detailed domain knowledge [4]. This integration is more than just cooperation; it's a merging of empirical data and human understanding to create solutions that are highly relevant and precise [5,6].

However, blending AI/ML with domain expertise is not without challenges. Successfully integrating domain knowledge into AI and ML models requires a deep understanding of both the technical mechanisms and the specific complexities of the domain [7]. Additionally, the ever-changing nature of domain knowledge and the rapid advancement of AI and ML technologies add further complexity to this process [8,9].

This introduction prepares the reader for a comprehensive exploration of AI and ML, emphasizing a strong commitment to utilizing domain knowledge [10]. It sets the stage for an in-depth journey through methodologies, collaborative strategies, ethical considerations, and future predictions, all aimed at unlocking the full potential of AI and ML when guided by specialized expertise [11,12].

The overarching purpose of this article is multifaceted, aiming not only to illuminate the synergistic potential of combining domain expertise with AI and ML but also to contribute original insights and methodologies to the field. Unlike previous works, this paper provides a comprehensive synthesis of existing knowledge and introduces new perspectives and practical frameworks that have not been collectively presented before (see Table 1).

Table 1. Key benefits of integrating domain knowledge in AI/ML.

Original Contribution	Description
Unified methodological framework	Development of a novel, structured framework that consolidates diverse methodologies for integrating domain knowledge into AI/ML, offering practitioners and researchers a unified approach not previously available in the literature [4].
Cross-industry case studies with new insights	Presentation of detailed case studies across various industries, including materials science, exoskeleton devices, and poverty estimation, providing fresh insights and highlighting applications of domain knowledge integration that extend beyond existing studies [5].
Practical tools and strategies	Introduction of actionable strategies and tools, such as advanced feature engineering techniques, knowledge graphs, and human-in-the-loop systems, offering original guidance for effectively embedding domain expertise into AI/ML models [6].
Ethical considerations and future trends	Original analysis of ethical implications and future trends related to domain knowledge integration in AI/ML, including discussions on handling dynamic domains and ensuring equitable AI performance, contributing new thought leadership to ongoing discourse [7].
Enhancement of AI/ML performance evidence	Provision of empirical evidence and arguments demonstrating how domain knowledge significantly enhances AI/ML model performance, interpretability, and applicability, offering new validation and expanding on the implications of this integration in various sectors [6].

Specifically, this article sets out to:

1. **Introduce a Novel Framework for Integrating Domain Knowledge into AI/ML**
By synthesizing existing methodologies and introducing new strategies, the article offers an original framework that enriches AI/ML applications with contextual depth and interpretative strength, providing a resource not previously consolidated in the field [8].
2. **Present Comprehensive, Cross-Industry Case Studies with Fresh Perspectives**
Through an original collection of meticulously curated case studies from diverse industries, including sectors not extensively covered in prior works, the article demonstrates the transformative impact of domain knowledge integration, offering readers new insights and practical examples [9].
3. **Offer Practical Guidance and Innovative Tools**
Recognizing the challenges inherent in merging technical models with human expertise, the article introduces new practical tools and methodologies, such as advanced prompt engineering and interpretable models, providing actionable strategies for practitioners and researchers [10].
4. **Provide Original Analysis of Ethical and Practical Considerations**
The article delves into the ethical implications of integrating domain knowledge, offering original perspectives on ensuring AI/ML solutions are socially responsible, ethically conscious, and aligned with human values, thereby expanding the conversation beyond technical aspects [7].
5. **Forecast Future Trends and Innovations**

By analyzing current developments and predicting future directions, the article provides original insights into upcoming innovations in AI and ML that prioritize domain knowledge, helping readers prepare for and navigate the evolving landscape [7].

This article aspires to be a seminal piece, catalyzing discourse and action among the AI/ML community by highlighting the indispensable role of domain knowledge and introducing original contributions that chart a course toward more informed, ethical, and impactful AI/ML solutions (see Figure 1).

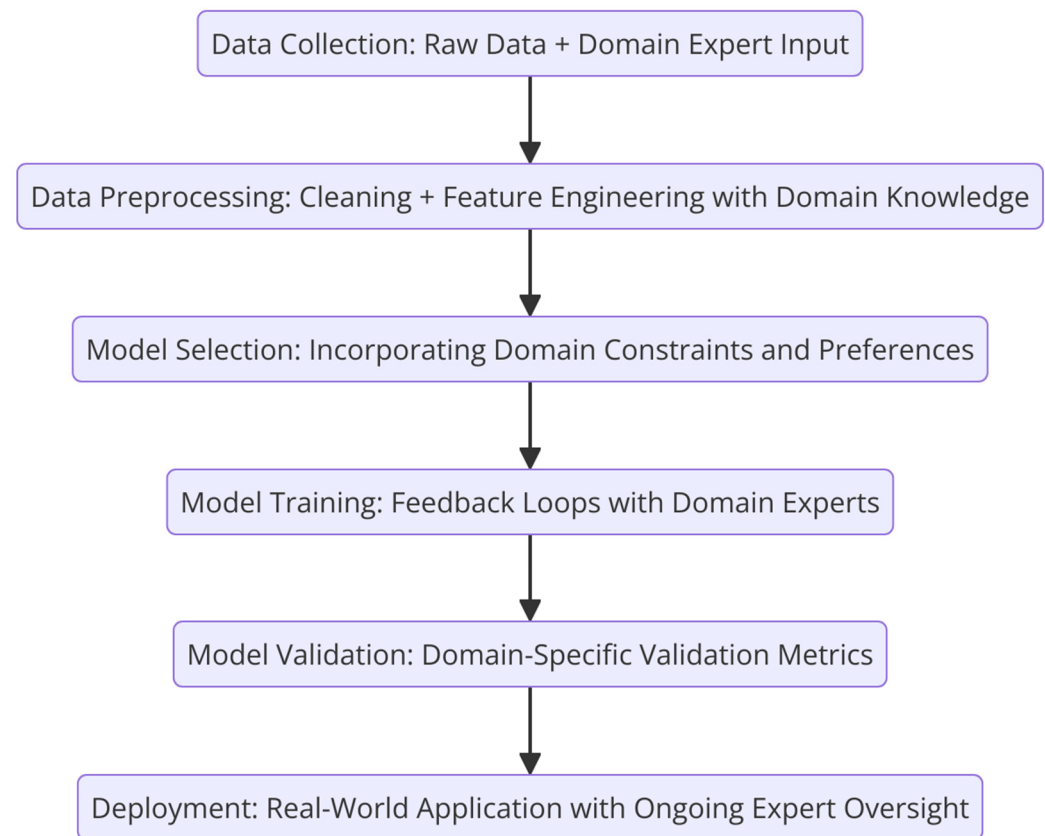


Figure 1. Integration of domain knowledge in AI/ML workflow.

2. The Synergy of AI/ML and Domain Knowledge

2.1. Understanding Domain Knowledge

At its core, domain knowledge represents the culmination of insights, experience, and intuitive understanding, all specific to a particular field or sector. It is the profound comprehension of the variables, intricacies, and dynamics that characterize a domain, be it healthcare, finance, manufacturing, or any other industry [13]. This knowledge encompasses not just the overt, quantifiable elements but also the tacit, often unspoken principles that govern the subtle nuances of the domain [14].

Domain experts, therefore, are not merely repositories of facts but are seasoned interpreters of their domain's unique language. They can discern patterns, predict trends, and make informed decisions that are deeply rooted in the contextual fabric of their specific field [15].

2.2. The Crucial Role of Domain Knowledge in AI/ML

In the realm of AI and ML, domain knowledge assumes a pivotal role, acting as the compass that guides the sophisticated algorithms towards meaningful, actionable insights [16].

While AI/ML can efficiently process and analyze vast datasets, domain knowledge is essential to imbuing the data with meaning [17]. It enables the distinction between

correlation and causation, ensuring that the patterns identified by algorithms resonate with the practical realities of the domain [18].

The process of feature engineering—selecting and transforming variables into inputs for machine learning models—is profoundly enriched by domain knowledge [1,4]. It ensures that the features are not just statistically significant but are also contextually relevant and aligned with domain-specific objectives [19].

Domain knowledge aids in selecting the appropriate AI/ML models and tailoring them to address the nuanced requirements of a specific domain [18]. It helps in setting realistic expectations, understanding the potential limitations [20], and making informed trade-offs between model complexity and interpretability [21].

AI/ML solutions, to be truly impactful, need to resonate with the end-users—the domain experts [16]. Incorporating domain knowledge ensures that the solutions are designed with a user-centric approach [17], fostering acceptance and ensuring that the insights generated are actionable and aligned with domain-specific workflows [22].

In many domains, especially those like healthcare and finance, decisions informed by AI/ML have profound ethical implications and are subject to stringent regulatory standards [23]. Domain knowledge is crucial to navigating this complex landscape, ensuring that the solutions adhere to ethical norms and comply with regulatory mandates [24,25].

The confluence of AI/ML with domain knowledge is not just beneficial but essential. It is a confluence that transforms raw data into wisdom, guiding algorithms to not just analyze but also to understand, and ensuring that the technological marvels of AI and ML are harnessed to their fullest potential, firmly grounded in the rich soil of human expertise and experience. $\mathcal{O}$

2.3. Case Studies

The significance of domain knowledge in AI/ML projects can be substantially appreciated through two distinct case studies: the use of mammography for breast cancer diagnosis and the training of robots for real-world tasks.

In the realm of healthcare, specifically in breast cancer diagnosis using mammograms, the inclusion of domain knowledge profoundly enhances the performance and interpretability of AI models. Traditionally, computer vision approaches to mammogram image analysis, like employing convolutional neural networks (CNNs), provide a solid baseline [26,27]. However, when domain-specific insights—such as understanding the importance of features like breast density asymmetry as an indicator of cancer—are integrated, the models become significantly more powerful. Researchers developed a multi-view, multi-task (MVMT) [28,29] system that mirrors the workflow of radiologists, predicting not only the diagnosis but also auxiliary targets like signs, suspicion, and breast density for each mammogram view. This approach not only improved the diagnostic accuracy (with the area under the ROC curve reaching 0.855, which is 0.018 higher than the baseline) [29] but also enhanced the model's interpretability and interaction with medical professionals. The domain knowledge contributed to a refined feature set, improved accuracy, and more meaningful interactions between the model and human experts.

In the field of robotics, the role of domain knowledge becomes evident in bridging the gap between simulated training environments and real-world applications, a process often termed “sim2real” [30] (see Table 2). Simulations, while crucial for training algorithms, cannot perfectly replicate real-world conditions. Domain knowledge assists in identifying and incorporating critical factors, such as actuator noise, into the simulations [31]. Actuator noise, representing the variability in a robot's movements or actions in the real world, is crucial for ensuring that the behavior of robots in simulations aligns with their real-world counterparts [30]. Research indicates that aligning the noise levels in simulations with those in the real world results in better performance of the robots, both in simulations and in real-world tasks [31,32]. This highlights the invaluable role of domain knowledge in creating more realistic and effective simulation environments for robotic training [32].

Table 2. Case studies: success stories of domain knowledge integration.

Industry	Case Study Description	Key Outcomes
Healthcare	Integration of domain knowledge in mammography for breast cancer diagnosis. By embedding medical expertise about breast tissue characteristics and cancer indicators into AI models, diagnostic accuracy was improved. Without incorporating this domain knowledge, AI models might miss subtle signs of cancer, leading to less accurate diagnoses.	Improved diagnostic accuracy
Manufacturing	Ford’s use of digital twins and predictive maintenance. By integrating engineering knowledge of machinery operations and failure patterns into AI systems, Ford optimized production stages and reduced downtime. Without domain-specific insights, AI might not accurately predict equipment failures or optimize maintenance schedules effectively.	Optimized production stages, reduced downtime, enhanced efficiency
Finance	Implementation of fair and transparent loan approval processes integrating domain expertise in financial risk assessment. By incorporating financial regulations and risk assessment principles, AI models reduced bias in loan approvals. Without domain knowledge, AI systems might perpetuate existing biases or overlook regulatory compliance, leading to unfair lending practices.	Reduced bias in loan approvals, increased trust in financial services
Retail	L’Oréal’s integration of diverse data sources like social media and weather patterns for demand forecasting. By applying knowledge of consumer behavior and market dynamics, the AI models accurately predicted demand. An AI system lacking this domain context might fail to correlate these diverse data points effectively, resulting in inaccurate forecasts and poor inventory management.	Accurate demand predictions, optimized inventory management
Robotics	Use of domain knowledge in sim-to-real transfers to align simulated training environments with real-world conditions for better robotic task performance. By incorporating physical laws and environmental factors into simulations, robots performed tasks more effectively in real-world settings. Without integrating domain knowledge, discrepancies between simulations and actual conditions could hinder robotic performance.	Improved real-world task performance, better alignment with simulations

The integration of domain knowledge in AI/ML processes, from the initial problem specification and data understanding to the final model evaluation and interpretation, significantly enhances the robustness, accuracy, and applicability of the models [33]. This integration ensures that the developed models not only excel in technical performance but also resonate with and are relevant to the specific needs and nuances of the domain they are intended for [34].

These case studies underline the transformative impact of incorporating domain expertise into AI/ML projects, emphasizing that the fusion of technical prowess with deep, contextual understanding results in solutions that are not only technically sound but also deeply aligned with the domain-specific realities and requirements.

3. Results and Discussion on the Limitations of AI/ML When Used Without Proper Contextual Understanding

When AI/ML is employed without a thorough contextual understanding, a cascade of limitations may arise, subtly undermining the performance, reliability, and reception of the models [8]. In scenarios devoid of domain expertise, there is a heightened risk of data misinterpretation [8,35]. Models might erroneously latch onto irrelevant patterns or noise, mistaking these for meaningful insights [36]. This jeopardizes not only the model’s precision but also its ability to generalize beyond the training data, rendering it less effective in real-world applications [37].

Moreover, the absence of domain knowledge can erode trust and hinder the adoption of AI/ML solutions [38,39]. Stakeholders and end-users, particularly in sectors with intricate and nuanced operational landscapes like healthcare [40] or finance [39], may be reluctant to embrace models that do not align with their experiential understanding or fail to address domain-specific constraints and expectations [41].

The ethical dimension is equally critical. Models ignorant of the contextual fabric may inadvertently perpetuate biases, propelling unfair or unethical outcomes [42]. This lack of sensitivity to the domain's ethical and societal fabric questions not only the model's fairness but also its acceptability and viability in real-world settings [43,44] (see Table 3).

Table 3. Challenges and solutions in integrating domain knowledge.

Challenge	Solution	Example
Communication gaps	Cross-disciplinary training and regular structured meetings	Workshops and collaborative platforms
Data misinterpretation	Involvement of domain experts in data preprocessing and feature engineering	Joint feature selection sessions
Dynamic knowledge evolution	Implementing continual learning and active learning strategies	Online learning models updating in real time
Ethical and regulatory compliance	Close collaboration with domain experts to ensure adherence to laws and ethical standards	Regular audits and compliance checks
Trust and adoption	Use of interpretable models and visualization tools to improve transparency	Interactive dashboards for end-users

Furthermore, the journey from problem identification to solution implementation becomes fraught with inefficiencies when stripped of domain insights. Models might chase after inaccurately defined problems or approach them in ways that are theoretically sound but practically inept [45,46]. The interpretability of these models, a crucial aspect especially in sensitive domains, suffers too. Without domain-specific lenses to view and interpret the model's outputs, the results might remain cryptic or misleading, complicating the task of effectively communicating and leveraging these insights for decision-making [47,48].

In essence, while AI/ML models are a powerhouse of potential, realizing this potential in a manner that is technically astute, ethically conscientious, and contextually resonant necessitates a harmonious blend of computational prowess with deep, domain-specific wisdom.

3.1. Bridging the Gap Between Data Scientists and Domain Experts

Bridging the gap between data scientists and domain experts is crucial for the success of AI/ML projects, yet it presents several challenges that stem from the diverse backgrounds, perspectives, and languages of these two groups.

1. **Differences in Terminology and Communication:** Data scientists and domain experts often speak different “languages” [49]. The technical jargon and complex statistical terms used by data scientists can be bewildering to domain experts who may be more familiar with industry-specific terminology [50]. This language barrier can lead to misunderstandings or misinterpretations of data insights or project requirements [51].

2. **Varied Approaches to Problem-Solving:** The two groups may have different approaches to problem-solving. Data scientists often focus on data-driven solutions and may prioritize model accuracy and computational efficiency [52]. In contrast, domain experts may emphasize practical feasibility, interpretability, and the broader context of the problem, including regulatory and ethical considerations [53].

3. Differing Expectations and Goals: There may be a misalignment in the expectations and end goals [54]. Data scientists might aim to develop the most advanced model, whereas domain experts might be more interested in actionable insights that fit into existing workflows and decision-making processes [55,56].

4. Challenges in Data Interpretation: Domain experts might lack the technical expertise to fully understand and interpret complex models and results presented by data scientists [57]. Conversely, data scientists might not fully appreciate the nuances and implications of the data without the domain-specific insights, leading to an oversimplified or incorrect interpretation of the data [58].

5. Collaboration and Trust Issues: Effective collaboration requires trust and mutual respect, which can be hindered by a lack of understanding of each other's expertise and contributions [59,60]. Building trust takes time and effort, and without it, collaboration can be strained, slowing down the progress of AI/ML projects [60,61] (Figure 2).

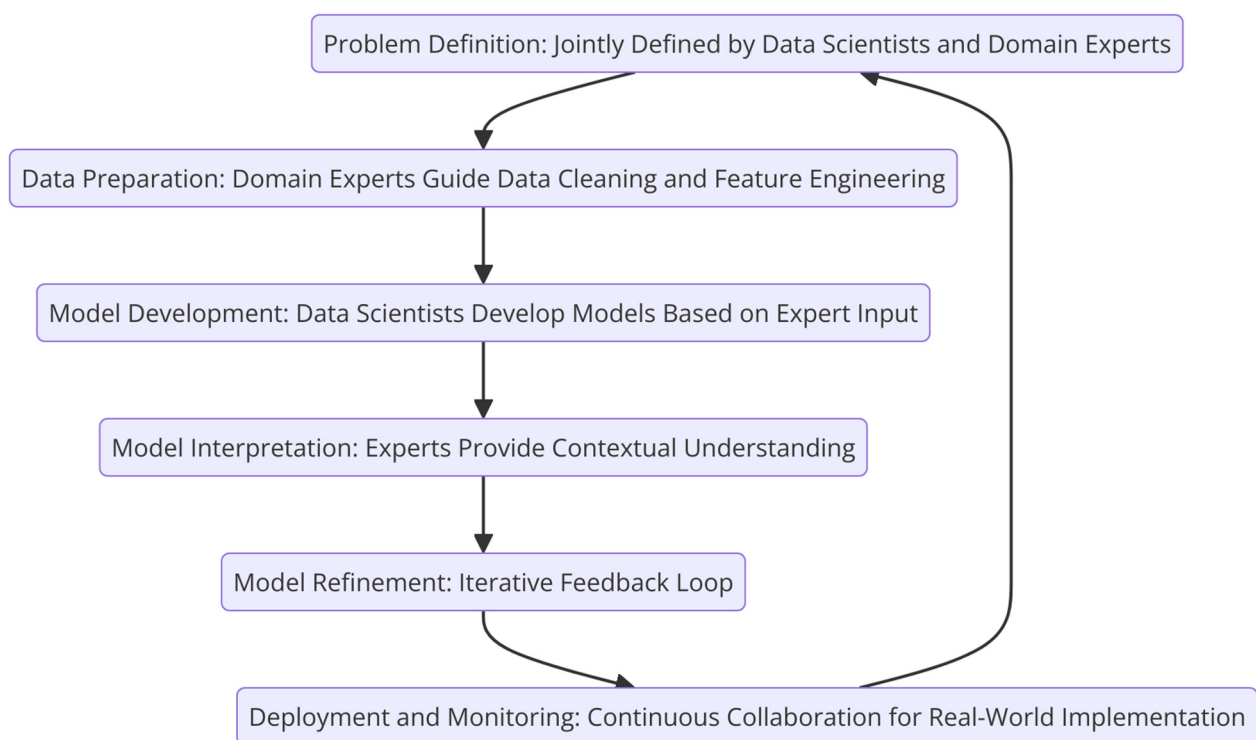


Figure 2. Collaborative cycle between data scientists and domain experts.

To overcome these challenges, it is important for both data scientists and domain experts to engage in open, frequent, and clear communication; appreciate each other's expertise; and work towards a common goal. Tools and methodologies that facilitate mutual understanding, like shared data visualization platforms or collaborative workshops, can also be instrumental in bridging this gap.

3.2. Strategies to Foster Effective Collaboration and Knowledge Sharing

Fostering a symbiotic collaboration between data scientists and domain experts necessitates an ecosystem where communication flourishes, mutual understanding is a norm, and the unique strengths of each discipline are harnessed synergistically [62]. At the heart of this ecosystem is the ethos of continuous learning and respect for each discipline's body of knowledge [63].

Cross-disciplinary training forms the bedrock of this collaborative landscape. It is not just about skimming the surface of each other's expertise but also about diving deep enough to appreciate the nuances and constraints that each domain operates within [63,64]. This mutual educational journey cultivates a common language, easing the often-turbulent

waters of technical communication. Regular, structured communication channels and meetings serve as the conduits for this ongoing dialogue [65]. These interactions are not mere formalities but vital platforms for dynamic knowledge exchange, where questions are encouraged, challenges are dissected, and solutions are collaboratively forged [66,67].

The power of visual tools and prototypes in this collaborative endeavor cannot be overstated. They act as bridges, translating complex data patterns and model predictions into a language that resonates with all stakeholders, regardless of their technical prowess [68]. This visual narrative not only demystifies the data but also catalyzes a shared understanding and alignment on the project's objectives and potential outcomes [69].

Establishing a shared glossary is akin to crafting a map for this collaborative journey [70]. It ensures that every team member, irrespective of their background, navigates the project landscape with a clear understanding of the terminology, reducing the fog of miscommunication and misinterpretation that can often derail collaborative efforts [71].

While tools and structured interactions form the skeleton of collaboration, the soul lies in recognizing and respecting the expertise that each individual brings to the table [72,73]. It is about creating an environment where the insights of a domain expert hold as much weight as the technical acumen of a data scientist, fostering a culture of mutual respect and trust [74].

The iterative feedback loops act as the pulse of the project, ensuring that the collaboration is not a one-off event but a continuous, dynamic interaction [75]. Feedback is not just sought but is actively incorporated, creating a model that is continuously refined and realigned with the practical, domain-specific realities and insights [76,77].

In this meticulously crafted ecosystem, the collaboration between data scientists and domain experts transcends the boundaries of mere cooperation. It evolves into a harmonious symphony of data-driven insights and domain-specific wisdom, driving AI/ML projects that are not only technically robust but are also deeply resonant with the practical, ethical, and contextual realities of the domain they aim to serve.

3.3. Tools and Techniques for Bridging the Gap

In the intricate dance of collaboration between data scientists and domain experts, a harmonious partnership is choreographed through the adept use of various tools and techniques, each playing a pivotal role in nurturing clear communication, fostering mutual understanding, and enhancing collaborative efficiency [77,78].

Visual storytelling emerges as a powerful tool in this ensemble, with data visualization platforms like Tableau [78] or Power BI transforming complex, abstract data into vivid, interactive visual narratives [79]. These platforms speak a universal language, transcending the barriers of technical jargon and making data insights accessible and engaging for all stakeholders, regardless of their data literacy levels [79,80].

The stage for collaboration is set on shared platforms such as GitHub [80] or Jupyter Notebooks [81], which serve as dynamic arenas where code, data, and insights converge. These platforms promote a culture of transparency and inclusivity, enabling every team member to contribute, review, and refine the collective work, ensuring that every voice is heard and every insight is valued [82,83].

Navigating the journey of a complex AI/ML project demands not just collaboration but also meticulous orchestration, a role adeptly fulfilled by project management tools like Trello or Asana [84]. These tools act as compasses, guiding the team through the labyrinth of tasks, deadlines, and goals, ensuring that every step taken is in alignment with the project's vision and objectives [85].

Collaboration extends beyond managing tasks and timelines; it thrives on meaningful communication and engagement. Tools like Slack [86] and Microsoft Teams [87] foster an environment where team members can share ideas, engage in discussions, and collaborate more effectively. These platforms encourage spontaneous exchanges, allowing for real-time feedback, the sharing of innovative solutions, and the collective insights that come from diverse perspectives [88].

In this collaborative odyssey, prototyping tools stand as the architects of imagination, transforming abstract concepts into tangible realities [80]. Tools like Sketch [85] or Figma [86] bring ideas to life, enabling stakeholders to interact with prototypes, to touch, feel, and experience the solutions before they are fully realized, ensuring that the final product is a reflection not just of data insights but also of the users' needs and expectations [89–95].

Efficiency in collaboration is not just about working harder but also about working smarter. Workflow automation tools like Apache Airflow [89] streamline the mundane, automating routine tasks and liberating the team to invest their time and talents in what truly matters—solving complex problems, uncovering deep insights, and innovating groundbreaking solutions [90–95].

Yet, in the whirlwind of collaboration, knowledge should not be fleeting. Knowledge repositories like Confluence serve as the collective memory of the team, preserving every insight, decision, and learning [96]. They ensure that knowledge is not just created but also shared, nurtured, and evolved, laying a strong foundation for not just the current project but for future endeavors as well [97,98].

In this rich tapestry of tools and techniques, every thread is integral, weaving together a collaborative masterpiece where data scientists and domain experts dance in perfect harmony, creating solutions that are not just technically robust but are also deeply resonant with the real world they aim to serve.

4. Methodologies for Integrating Domain Knowledge into AI/ML

In the field of artificial intelligence (AI) and machine learning (ML), integrating domain knowledge into model development is crucial for enhancing performance, interpretability, and applicability in real-world scenarios [99,100]. This chapter explores methodologies for incorporating domain expertise throughout various stages of the AI/ML pipeline, including data preprocessing, feature engineering, model selection, and handling dynamic domains where knowledge evolves over time.

4.1. Techniques for Incorporating Domain Expertise

Feature Engineering

Feature engineering is a critical step where raw data are transformed into meaningful inputs for AI/ML models [101]. Utilizing domain knowledge significantly enhances feature selection and engineering, improving model performance. Techniques such as knowledge graphs can refine feature selection processes, particularly in fields like biomedical research and natural language processing [95]. Knowledge graphs allow for the representation of complex relationships between entities, enabling the extraction of features that capture the underlying structure of the data.

Effective preprocessing techniques, including data cleaning and normalization, are essential for optimizing AI modeling pipelines [96]. Domain experts play a pivotal role in identifying and handling anomalies, missing values [102], or outliers in ways that are meaningful within the context of the domain [103]. They ensure that data transformations preserve the integrity of the information and do not introduce bias or distort underlying relationships [103,104].

The integration of domain knowledge allows for the identification of relevant features that can lead to more accurate predictions [97]. For instance, in medical diagnostics, understanding the clinical significance of certain biomarkers can guide the inclusion or exclusion of features, enhancing both model performance and interpretability.

Exploratory Data Analysis (EDA)

Exploratory data analysis is a process of analyzing datasets to summarize their main characteristics, often using visual methods [105]. AI and ML can automate aspects of EDA, enhancing the identification of valuable insights and patterns within data. Automation

of EDA improves feature importance ranking and selection, which is crucial for robust predictive modeling [98].

Advanced techniques, such as tree-based models and clustering algorithms, facilitate the detection of anomalies and hidden groupings, enriching the analysis [99]. However, effective utilization of these methods requires a deep understanding of the algorithms and their limitations, alongside domain expertise for proper interpretation [100]. Domain experts provide context to observed patterns, discerning whether they are meaningful or artifacts of the data collection process [106–109].

Model Selection

Selecting the appropriate model significantly impacts the performance and applicability of AI/ML solutions [109]. Incorporating domain knowledge into model selection leads to more accurate predictions, particularly in applications like healthcare decision support systems [101]. Domain experts, with their deep understanding of the problem, provide invaluable insights into which model architectures are likely to capture complex relationships in the data [109].

They highlight trade-offs between model complexity and interpretability pertinent to their domain, guiding the selection of a model that not only performs well but also aligns with operational and regulatory constraints [109,110]. The integration of domain expertise helps in tuning model parameters effectively, essential for achieving optimal performance in specific contexts [102]. Furthermore, explainable AI techniques enhance model transparency, allowing domain experts to understand and trust AI predictions [103].

In these processes, collaboration between data scientists and domain experts is a dynamic, iterative dialogue. The technical expertise of data scientists is enriched by domain insights, ensuring every step of the AI/ML pipeline is informed, intentional, and aligned with the domain it serves.

4.2. Approaches to Encoding Domain Knowledge

Encoding domain knowledge into AI/ML models transforms complex, domain-specific insights into explicit rules or constraints that guide the model [110,111]. This ensures models not only learn from data but also resonate with established domain principles [111,112].

Explainable AI (XAI)

Explainable AI focuses on making AI models more transparent and understandable to humans. Integrating domain knowledge into XAI frameworks enhances model transparency and user understanding, facilitating better decision-making. This integration allows AI systems to provide human-understandable explanations for their processes, crucial in safety-critical applications like healthcare and finance [104].

By combining XAI explanations with domain knowledge, users can evaluate model performance more effectively, leading to improved trust and usability [100]. Reasoning-based approaches to XAI, such as interpretable models utilizing logical rules, significantly enhance AI interpretability [105].

Prompt Engineering

In large language models (LLMs), prompt engineering is critical for embedding domain knowledge to improve classification tasks, especially in data-scarce scenarios [101]. This approach involves crafting specific prompts that guide model responses, leveraging pre-existing knowledge without altering parameters [106]. Advanced techniques like few-shot and chain-of-thought prompting enhance model performance across applications, including education and healthcare [107]. Social prompt engineering initiatives aim to democratize prompt design, making it accessible to non-experts [108].

Interpretable Models

Using interpretable machine learning models allows for encoding domain knowledge through logical rules, enhancing explainability [105–111]. Models like decision trees and

rule-based systems are designed to be understandable by humans, suitable for applications where transparency is essential [109,112–116]. Integrating domain knowledge improves accuracy and reliability, particularly in complex decision-making environments [102,117–119]. For example, in financial modeling, incorporating regulatory rules ensures predictions adhere to legal requirements.

Both rule-based and constraint-based models aim to keep AI/ML models grounded in domain reality and wisdom. This blend of computational intelligence and human expertise creates models that are powerful, trustworthy, and meaningful [120].

4.3. Handling Dynamic Domains Where Knowledge Evolves over Time

Handling dynamic domains where knowledge evolves is a significant challenge in AI/ML. Models must understand the current state of knowledge [121] and adapt to new information, trends, and patterns as they emerge [122], requiring a flexible, responsive approach to development and maintenance [123].

Adaptive Learning

Adaptive learning is essential for AI systems in dynamic domains like healthcare, where data and knowledge continuously evolve. Systems must learn from new data inputs to maintain predictive accuracy and relevance [110]. Techniques such as online learning and reinforcement learning allow models to update parameters in real time, responding to changes in data distributions [5]. Continuous monitoring and risk assessment are crucial for identifying model drift, ensuring AI systems remain reliable [97].

Building models that learn incrementally, updating parameters and structure with new data [124], is effective. Online learning or continual learning techniques allow for adaptation over time without retraining from scratch, preserving existing knowledge while incorporating new insights [122–127].

Knowledge Integration

Employing ontology and natural language processing (NLP) techniques aids in dynamically updating domain models, keeping them relevant as knowledge evolves [111]. Ontologies provide structured frameworks for representing domain knowledge, facilitating the integration of new information and relationships [112]. NLP techniques assist in extracting insights from unstructured data sources like research articles and clinical notes, enabling timely knowledge base updates [113]. This is particularly important in fast-paced fields like medicine, where new treatments and guidelines frequently arise.

Constraint-based models offer a subtle approach to integrating domain knowledge. Instead of explicit rules, these models incorporate constraints or conditions that solutions must adhere to [117,118]. These constraints, rooted in domain understanding, ensure outputs are statistically valid, practically feasible, and domain-compliant [118,119]. For instance, in optimization problems, constraints ensure solutions respect physical limitations or resource availability typical to the domain [119,120].

Collaborative Data Understanding

Collaborative data understanding involves domain experts working alongside AI systems to curate datasets, addressing biases and ensuring models are trained on relevant, representative data [100] (Holstein, 2024). This collaboration enhances training data quality, leading to improved model performance and fairness [114] (Gonzalez, 2023). Engaging experts in data curation fosters a deeper understanding of model limitations and potential biases, allowing for informed decision-making [115] (Miller, 2022). Participatory approaches empower stakeholders, ensuring AI applications align with ethical standards and societal values [116].

Regular monitoring and evaluation of model performance are crucial. This helps identify when performance degrades due to domain changes and provides insights into domain evolution and model adaptation needs [16,17].

In essence, handling dynamic domains requires advanced AI/ML techniques, flexible system design, and ongoing partnerships between models and domain experts. Together, these ensure AI/ML systems remain effective, relevant, and valuable as knowledge landscapes shift and evolve [128–131].

5. Case Studies: Success Stories and Lessons Learned

5.1. Detailed Case Studies from Various Industries

The successful integration of domain knowledge in AI/ML is vividly demonstrated across various industries, each showcasing innovative applications and transformative outcomes. These case studies highlight the profound impact of embedding specialized knowledge into AI systems, addressing complex challenges, and enhancing decision-making processes.

Materials Science

The study “Embedding Domain Knowledge for Machine Learning of Complex Material Systems” by Childs (2019) [117] explores the integration of domain knowledge into ML applications within materials science. Materials systems often suffer from limited datasets, hindering the effectiveness of traditional ML algorithms that rely on large amounts of data. By embedding domain knowledge, researchers can significantly reduce data requirements for training ML models, making it feasible to apply these techniques to a broader range of materials. This approach not only enhances model performance but also improves interpretability, providing clearer explanations of how various factors influence material properties. The study reviews strategies for embedding domain knowledge, offering examples of their implementation in ML algorithms and discussing applications across different materials systems.

Manufacturing Sector

In the manufacturing sector, integrating domain knowledge into AI systems has proven essential for optimizing processes and achieving significant performance gains. The study by Chen (2022) [109] presents an innovative approach to integrating human expert knowledge into neural network models to enhance decision-making in manufacturing processes. The interpretable neural network (INN) model incorporates domain knowledge as interpretable features and rules, crucial for constructing rule-based systems that support manufacturing decision-making, such as process modeling and quality inspection. By using a center-adjustable sigmoid activation function, the INN efficiently optimizes these rule-based systems, ensuring predictions are accurate and interpretable by human experts. This approach addresses the limitations of traditional ML models, which often lack transparency and are difficult for domain experts to understand.

Companies like Ford have utilized AI-based predictive maintenance through digital twins, incorporating detailed engineering knowledge about machinery operations and failure modes. By embedding specialized information, AI models can more accurately predict equipment failures and optimize maintenance schedules, leading to reduced downtime and energy savings that generic AI models without such knowledge might miss [132]. Without integrating domain-specific insights, AI might not effectively interpret machine behaviors, resulting in less efficient maintenance strategies.

Similarly, L'Oréal leverages AI for demand forecasting by integrating domain knowledge about consumer behavior and market dynamics. Utilizing diverse data sources like social media trends, point-of-sale data, and weather patterns, and understanding how these factors influence purchasing decisions, AI models can more precisely predict demand and optimize market strategies. An AI system without this domain context might fail to correlate diverse data points effectively, leading to inaccurate forecasts and suboptimal inventory management [132,133].

The study by Obiuto (2024) [118] discusses the transformative role of AI in construction management. It highlights how AI technologies, particularly predictive analytics and ML, are leveraged to address common challenges such as project complexity, delays, and

communication issues. Through various case studies, the paper showcases successful implementations of AI, demonstrating significant benefits like increased project efficiency, cost savings, and improved safety. These examples illustrate how AI can optimize project planning, scheduling, and risk management, leading to more streamlined and effective construction processes.

Healthcare

In healthcare, integrating domain knowledge into AI systems has been pivotal in revolutionizing clinical operations and patient care. The Mayo Clinic's partnership with Google Cloud exemplifies the profound impact of integrating AI and ML from the ground up. Their collaboration focused on creating a solid data and infrastructure foundation to make healthcare data more meaningful, accessible, and interoperable [128]. This partnership facilitated patient care and empowered research and the discovery of new cures. The initiative was built upon a "three-layer cake" strategy, encompassing a core build, data foundations, a software delivery pipeline, data migration, security operations, IT operations [129], and an AI factory, all contributing to supporting AI and ML with an advanced model development environment [130]. This comprehensive approach allowed for the integration of clinical, operational, and financial data, facilitating a holistic view of the patient journey and enabling the effective use of AI and ML in advancing healthcare [131].

The research "Human-in-the-Loop Machine Learning: A Survey" by Kim (2015) [119] explores integrating human expert knowledge into ML models, particularly in high-stakes domains like medical decision-making. This approach emphasizes the importance of human expertise in enhancing ML systems' performance and reliability, especially when decisions significantly impact patient outcomes. Frameworks that facilitate collaboration between human experts and ML algorithms allow for a more interactive and iterative learning process. By incorporating feedback from domain experts, models can be refined to better reflect real-world complexities that purely data-driven approaches might overlook, improving accuracy and interpretability.

Similarly, the study by Schaekermann (2024) [120] develops a framework to assess the performance equity of health AI technologies. The framework quantitatively evaluates how AI models perform across different demographic groups, addressing potential disparities in healthcare outcomes. By incorporating domain knowledge, the framework ensures AI technologies do not inadvertently exacerbate existing inequities in healthcare, contributing to more equitable healthcare delivery.

The collaboration between TidalHealth Peninsula Regional and IBM implemented an AI-based clinical decision support system incorporating medical expertise and clinical protocols. By embedding detailed knowledge about disease presentations, diagnostic procedures, and treatment guidelines, the AI solution streamlined information searching, significantly reducing the time required for clinical searches. This integration allows medical professionals to access precise and relevant information quickly, which generic AI systems without such knowledge might not efficiently provide, enabling clinicians to dedicate more time to patient care [134–138].

Finance and Accounting

In the finance sector, the study by Kumari (2024) [121] investigates the transformative impact of AI and ML on portfolio management. The research highlights how these technologies revolutionize investment strategies by enabling more precise data analysis and prediction capabilities. AI-driven techniques such as reinforcement learning, natural language processing, and sentiment analysis are employed to develop dynamic and adaptive investment strategies. These methods allow continuous portfolio adjustments in response to real-time market conditions, optimizing asset allocation and risk diversification. The integration of AI not only enhances the ability to predict market trends with unprecedented accuracy but also improves overall efficiency and cost-effectiveness of investment strategies.

The review by Adelakun (2024) [122] explores AI applications in fraud detection within accounting. ML algorithms identify patterns and anomalies in financial data that could indicate fraudulent activity. Supervised learning models are trained on labeled datasets to distinguish between fraudulent and non-fraudulent transactions, while unsupervised learning models detect anomalies without prior labeling. Natural language processing (NLP) analyzes textual data like emails and financial documents to uncover suspicious activity and hidden relationships, particularly useful in forensic accounting. Case studies demonstrate AI's potential to enhance the accuracy, efficiency, and effectiveness of fraud detection efforts in accounting.

Energy Sector

The study by Chen (2023) [113] explores integrating prior knowledge with data-driven methods to enhance ML robustness in energy-efficient building engineering. Employing a component-based machine learning (CBML) approach, the research encodes building structural knowledge as semantic information within the model, allowing for more efficient data utilization and improved model robustness. The method significantly enhances ML model performance, even with sparse data inputs, by improving their ability to generalize from small and inconsistent datasets. The approach reduces training time and increases interpretability, making models more practical for real-world applications.

Poverty and Welfare Domain

The research "Satellite Image and Machine Learning based Knowledge Extraction in the Poverty and Welfare Domain" by Hall (2022) [112] investigates using satellite imagery combined with ML to estimate poverty levels. The study emphasizes the critical role of domain knowledge in enhancing model transparency and explainability. By integrating domain expertise, the research aims to improve the interpretability of ML predictions, essential for gaining acceptance and trust within the development community. The findings suggest domain knowledge is vital for achieving scientific consistency and for broader dissemination of these technologies in poverty measurement, bridging the gap between complex ML models and practical applications in poverty and welfare.

Exoskeleton Devices

The study by Han (2024) [123] explores integrating AI to improve human-machine interaction in medical exoskeletons. AI technologies, including ML, NLP, and predictive analytics, significantly enhance the efficiency and comfort of these devices. Machine learning algorithms analyze sensor data in real time, optimizing control strategies to adapt to user movements, improving user comfort and rehabilitation outcomes. NLP facilitates intuitive control through voice commands, reducing cognitive and physical burden on users. Predictive analytics anticipates user needs, enhancing exoskeleton responsiveness and minimizing error risk. Case studies of AI-integrated exoskeletons like the EksoGT and ReWalk demonstrate improved rehabilitation outcomes and user satisfaction.

Explainable AI (XAI)

The study by Feustel (2024) [104] presents a novel approach to integrating domain knowledge with XAI through a dialogue system. Focusing on improving user understanding and evaluation of AI model performance by combining XAI explanations with domain-specific insights, the dialogue system leverages computational argumentation techniques to incorporate domain knowledge into human-machine interactions. This integration allows users to explore different types of explanations and understand underlying AI decision-making processes more effectively. Implemented in a prototype system evaluated by users, the inclusion of domain knowledge enhances users' ability to assess model performance, underscoring the potential of dialogue systems to enhance AI model transparency and explainability.

Quantifying the Impact of Domain Knowledge

The study by Yang (2020) [116] investigates the role of domain knowledge in enhancing ML models, focusing on quantifying its contribution to performance. Employing methods like the Shapley value from cooperative game theory, the study provides a systematic approach to evaluating how much domain knowledge contributes to overall model effectiveness. Demonstrating that incorporating domain knowledge significantly enhances model accuracy, robustness, and interpretability, the research highlights the potential for domain knowledge to reduce training data requirements, making ML applications more efficient and accessible in fields with limited data availability.

Machine Learning Frameworks Incorporating Domain Knowledge

The case study by Yu (2010) [124] presents a novel framework for integrating prior domain knowledge into inductive ML, specifically through a variant of support vector machines (SVMs) known as a VQSVM (vector quantized support vector machine). Addressing critical ML challenges like consistency, generalization, and convergence, embedding domain knowledge enhances model predictions even with limited training data. The framework improves generalization, allowing the model to perform well on unseen data by leveraging domain insights, leading to faster convergence rates during training. This illustrates the potential of combining traditional ML techniques with domain expertise to create more effective and reliable predictive models.

These case studies across healthcare, manufacturing, finance, energy, and other sectors demonstrate how the successful integration of domain knowledge into AI/ML leads to significant improvements in efficiency, innovation, and decision-making. They highlight the difference between generic AI applications and those enriched with domain-specific expertise, showing that the latter provides more accurate, reliable, and actionable insights necessary for critical decisions.

5.2. Discussion on Challenges Faced and How They Were Overcome

In the case studies from healthcare and manufacturing, while the successful integration of AI/ML with domain knowledge led to significant advancements, it also presented unique challenges [139]. These challenges were addressed through strategic planning, collaborative efforts, and innovative problem-solving [140].

In the healthcare sector, particularly in the partnership between the Mayo Clinic [128] and Google Cloud [94,129], challenges included dealing with the complexity of healthcare data, ensuring interoperability, and maintaining the security and privacy of patient data [112]. To overcome these challenges, a comprehensive approach was taken, focusing on building a solid data infrastructure, ensuring data interoperability, and establishing stringent security operations [141]. Key takeaways include the importance of a robust foundational setup for data and infrastructure, the need for thorough data harmonization, and the critical role of security in managing sensitive healthcare data [128,129]. The detailed strategic layers, referred to as the “three-layer cake” strategy, emphasize the necessity of a structured, layered approach in dealing with complex healthcare data and integrating AI/ML solutions [141–143].

In the manufacturing industry, companies like Ford [144], L’Oréal, BMW, and General Motors [144,145] faced challenges related to predicting maintenance needs, optimizing production processes, and enhancing product quality through AI/ML integration. The challenges were addressed by creating digital twins for predictive maintenance, utilizing diverse data sources for accurate demand forecasting, and implementing AI in production processes for efficiency and innovation [135]. The key lessons learned include the value of predictive analytics in maintenance and quality control, the importance of leveraging diverse data sources for accurate forecasting, and the transformative potential of AI in redefining product development and production processes [136]. These case studies underline the significance of tailored AI solutions that are deeply integrated with domain-specific knowledge to drive operational excellence and innovation in manufacturing [137,145].

In the healthcare field, institutions like TidalHealth Peninsula Regional [137] tackled the challenge of time-consuming clinical searches by partnering with IBM to implement AI in clinical decision support. This initiative drastically reduced the time required for clinical searches, freeing up valuable time for medical professionals to focus on patient care [138]. The takeaway from this case study is the profound impact of AI in optimizing time-consuming processes, thereby enhancing the efficiency and effectiveness of healthcare delivery [146].

Overall, these case studies across healthcare and manufacturing industries demonstrate that while the integration of AI/ML with domain knowledge presents challenges, these can be effectively addressed through strategic planning, collaboration, and a focus on addressing domain-specific needs. The success stories underscore the transformative potential of AI/ML when combined with deep domain expertise, leading to enhanced operational efficiency, innovation, and improved outcomes.

5.3. Ethical Considerations and Responsible AI

The integration of domain knowledge in AI/ML practices is not only a catalyst for innovation and efficiency but also a pillar for ensuring ethical responsibility [147]. The nuanced understanding that domain experts bring can be instrumental in addressing ethical considerations and ensuring that AI/ML models adhere to principles of fairness, transparency, and accountability [148] (Figure 3).

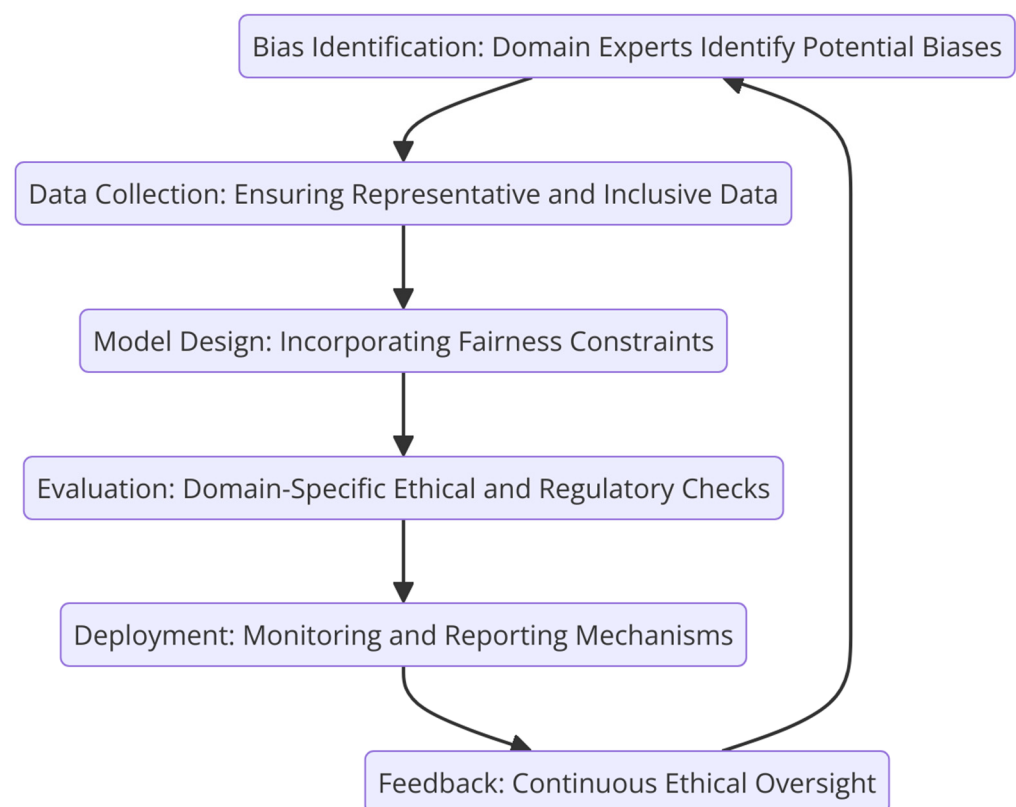


Figure 3. Ethical AI/ML development with domain expertise.

1. Role of Domain Knowledge in Ensuring Ethical AI/ML Practices:

Domain experts, with their deep understanding of the specific context and nuances of their field, play a crucial role in defining which ethical considerations are pertinent in a particular application of AI/ML [147,148].

They can identify potential ethical pitfalls that might not be apparent to data scientists or AI developers, such as scenarios where the model's application could lead to unintended consequences or where the data might be reflecting historical biases [142–154].

2. Addressing Bias and Ensuring Fairness:

AI/ML models are only as unbiased as the data they are trained on [146]. Domain experts can identify and mitigate biases present in the data, ensuring that the models do not perpetuate or exacerbate these biases [152].

They can guide the process of collecting more representative and inclusive data and can also provide insights into how different variables might be proxies for sensitive attributes, helping in the design of fairer models [145,146].

3. Legal and Societal Implications:

Domain experts understand the regulatory and legal frameworks that govern their fields [155]. This knowledge is crucial in ensuring that AI/ML applications comply with existing laws and regulations, avoiding legal repercussions and maintaining public trust [156].

They can foresee the societal implications of deploying AI/ML solutions, ensuring that these technologies are used in a way that benefits society and does not lead to negative outcomes, such as job displacement or erosion of privacy [149,150].

4. Importance of Informed, Domain-Aware AI/ML Applications:

Informed and domain-aware AI/ML applications are those that are developed and deployed with a deep understanding of the domain context, the stakeholders involved, and the potential impacts of the technology [151–158].

Such applications are more likely to be accepted by the end-users, as they are tailored to meet the specific needs and challenges of the domain, and they are also more likely to be ethical and fair, as they are designed with a nuanced understanding of what those concepts mean in the specific context [159–162].

Domain knowledge is not just an add-on but a fundamental component in the responsible and ethical development and deployment of AI/ML solutions [163]. It ensures that these powerful technologies are harnessed in a way that is socially responsible, legally compliant, and ethically sound, leading to outcomes that are beneficial and just for all stakeholders involved [164].

5.4. Future

The fusion of domain knowledge with AI/ML is poised to enter an exciting phase, marked by technological advancements and an evolving role for domain experts [7]. Emerging tools and technologies are increasingly facilitating this integration, making it more seamless and impactful [7,127]. As we look toward the future, we see an array of sophisticated tools like knowledge graphs, natural language processing, and automated reasoning becoming more prevalent [8,164]. These tools are not just enhancing the AI/ML models' understanding of complex domain-specific data but also enabling them to reason and make decisions in ways that closely mimic human expertise [164].

The role of domain experts is simultaneously evolving. As AI/ML systems become more sophisticated, the expertise of these professionals is becoming more crucial [34,147]. Domain experts are expected to take on more strategic roles, guiding the AI/ML systems not just in understanding the data but also in contextualizing the models' outputs, ensuring that they align with real-world applications and ethical considerations [114,164]. Their insights are becoming invaluable in training AI/ML models to navigate the intricate nuances of various domains, ensuring that the technology is applied in a way that is beneficial, ethical, and maximally effective [114,126].

Looking ahead, the collaboration between AI/ML and domain expertise is predicted to become even more intertwined [8,126]. We can expect to see a rise in collaborative platforms where domain experts and AI/ML developers work together seamlessly, each contributing their unique skills and knowledge [43]. The AI/ML systems of the future will likely be characterized by their ability to learn not just from data but also from the rich experience and insights provided by human experts [124]. This collaboration is poised to drive innovation across sectors, leading to AI/ML solutions that are not only technologically advanced but

also deeply ingrained with human wisdom and ethical considerations, ultimately leading to outcomes that are transformative, responsible, and aligned with the greater good [125,163].

6. Conclusions

In conclusion, the integration of domain knowledge into AI/ML is not just a trend but a fundamental shift towards creating more ethical, effective, and contextually relevant solutions. Throughout the discussed case studies and the exploration of emerging tools, it is clear that this integration is pivotal for advancing technology in a way that aligns with human values and real-world complexities.

The challenges and successes of these integrations in sectors like healthcare and manufacturing demonstrate the transformative potential of AI/ML when combined with deep learning. The integration of domain knowledge into artificial intelligence (AI) and machine learning (ML) represents a pivotal advancement in developing intelligent systems that are not only technically proficient but also contextually aware and ethically sound. This comprehensive exploration of methodologies and case studies underscores the multifaceted benefits of embedding domain expertise throughout the AI/ML lifecycle.

From the detailed analyses across various industries—such as healthcare, manufacturing, finance, energy, and beyond—it is evident that domain knowledge significantly enhances model performance, interpretability, and applicability. In healthcare, for instance, the collaboration between AI technologies and medical expertise has led to more accurate diagnostics, personalized treatment plans, and equitable healthcare delivery. The Mayo Clinic's partnership with Google Cloud and studies like those by Kim (2015) [119] and Schaekermann (2024) [120] exemplify how integrating clinical knowledge into AI systems can revolutionize patient care and research.

In manufacturing, the incorporation of specialized engineering knowledge into AI models has optimized processes, reduced downtime, and fostered innovation. Studies like the one by Chen (2022) [109] demonstrate how interpretable neural networks that embed domain knowledge can enhance decision-making in manufacturing processes. Similarly, in finance and accounting, embedding domain expertise into AI systems has improved investment strategies and fraud detection, as highlighted by Kumari (2024) [121] and Adalakun (2024) [122].

The methodologies discussed—including feature engineering with domain knowledge, knowledge graphs and ontologies, human-in-the-loop systems, active and continual learning, and model interpretability tools—provide practical frameworks for effectively embedding domain expertise into AI/ML systems. These approaches not only improve model accuracy and efficiency but also enhance transparency and trustworthiness, which are crucial for user acceptance and ethical considerations.

Handling dynamic domains where knowledge evolves over time remains a significant challenge. Adaptive learning techniques and continuous collaboration with domain experts are essential to ensuring AI systems remain relevant and effective. The use of ontologies and NLP techniques, as discussed in studies like those by Slihte (2017) [111] and Zhang (2023) [164], facilitates the dynamic updating of domain models, ensuring they keep pace with the latest developments.

The challenges associated with integrating domain knowledge—such as managing the complexity of knowledge representation, ensuring data quality, and maintaining ethical standards—highlight the necessity for ongoing collaboration between domain experts and AI practitioners. Addressing these challenges requires flexible system designs, continuous learning mechanisms, and robust frameworks that can adapt to new information and changing conditions.

Looking ahead, the synergy between AI/ML technologies and domain expertise is poised to drive significant advancements across various sectors. The future of AI/ML lies in systems that are not only data-driven but also enriched with human insights, capable of understanding and responding to the complexities of real-world environments. This evolution necessitates a multidisciplinary approach, bringing together technologists, domain

experts, ethicists, and stakeholders to co-create solutions that are innovative, responsible, and aligned with societal values.

The implications of this integration are profound. By embedding domain knowledge into AI/ML systems, we can achieve more accurate predictions, better decision-making processes, and solutions tailored to specific contexts. This leads to enhanced efficiency, cost savings, and improved outcomes in critical areas such as healthcare, finance, energy management, and social welfare.

The journey towards fully integrating domain knowledge into AI/ML is ongoing and demands concerted efforts from both the AI community and domain specialists. The success stories and methodologies highlighted in this work serve as a roadmap for future endeavors. By embracing this collaborative approach, we can unlock the full potential of AI/ML technologies, ensuring they serve as powerful tools for innovation while upholding ethical standards and addressing the nuanced needs of various domains. The fusion of computational power with human expertise is not merely an enhancement but also a necessity for creating AI/ML solutions that are truly effective, ethical, and aligned with human values.

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References

1. Gupta, R.; Srivastava, D.; Sahu, M.; Tiwari, S.; Ambasta, R.K.; Kumar, P. Artificial Intelligence to Deep Learning: Machine Intelligence Approach for Drug Discovery. *Mol. Divers.* **2021**, *25*, 1315–1360. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Angelov, P.P.; Soares, E.A.; Jiang, R.; Arnold, N.I.; Atkinson, P.M. Explainable Artificial Intelligence: An Analytical Review. *WIREs Data Min. Knowl. Discov.* **2021**, *11*, e1424. [\[CrossRef\]](#)
3. Woschank, M.; Rauch, E.; Zsifkovits, H. A Review of Further Directions for Artificial Intelligence, Machine Learning, and Deep Learning in Smart Logistics. *Sustainability* **2020**, *12*, 3760. [\[CrossRef\]](#)
4. Rädler, S.; Berardinelli, L.; Winter, K.; Rahimi, A.; Rinderle-Ma, S. Bridging MDE and AI: A Systematic Review of Domain-Specific Languages and Model-Driven Practices in AI Software Systems Engineering. *Softw. Syst. Model.* **2024**. [\[CrossRef\]](#)
5. Jan, Z.; Ahamed, F.; Mayer, W.; Patel, N.; Grossmann, G.; Stumptner, M.; Kuusk, A. Artificial Intelligence for Industry 4.0: Systematic Review of Applications, Challenges, and Opportunities. *Expert. Syst. Appl.* **2023**, *216*, 119456. [\[CrossRef\]](#)
6. Sundberg, L.; Holmström, J. Fusing Domain Knowledge with Machine Learning: A Public Sector Perspective. *J. Strateg. Inf. Syst.* **2024**, *33*, 101848. [\[CrossRef\]](#)
7. Rane, N.L.; Rane, J.; Paramesha, M.; Kaya, Ö. Emerging Trends and Future Research Opportunities in Artificial Intelligence, Machine Learning, and Deep Learning. In *Artificial Intelligence and Industry in Society 5.0*; Deep Science Publishing: Mumbai, India, 2024. [\[CrossRef\]](#)
8. Blasch, E.; Pham, T.; Chong, C.-Y.; Koch, W.; Leung, H.; Braines, D.; Abdelzaher, T. Machine Learning/Artificial Intelligence for Sensor Data Fusion—Opportunities and Challenges. *IEEE Aerosp. Electron. Syst. Mag.* **2021**, *36*, 80–93. [\[CrossRef\]](#)
9. Mourtzis, D.; Wang, L. Industry 5.0: Perspectives, Concepts, and Technologies. In *Manufacturing from Industry 4.0 to Industry 5.0*; Elsevier: Amsterdam, The Netherlands, 2024; pp. 63–96. [\[CrossRef\]](#)
10. Ijiga, O.M.; Idoko, I.P.; Ebiega, G.I.; Olajide, F.I.; Olatunde, T.I.; Ukaegbu, C. Harnessing Adversarial Machine Learning for Advanced Threat Detection: AI-Driven Strategies in Cybersecurity Risk Assessment and Fraud Prevention. *Open Access Res. J. Sci. Technol.* **2024**, *11*, 001–024. [\[CrossRef\]](#)
11. Tan, X.J.; Mustafa, N.; Mashor, M.Y.; Ab Rahman, K.S.; Wan Muhamad, W.Z.A.; Leow, W.Z.; Cheor, W.L.; Oung, Q.W. Understanding Domain Knowledge in Initialization Method for K-Mean Clustering Algorithm in Medical Images. In Proceedings of the 6th International Conference on Electrical, Control and Computer Engineering: InECCE2021, Kuantan, Malaysia, 23 August 2022; pp. 805–817. [\[CrossRef\]](#)

12. Dash, T.; Chitlangia, S.; Ahuja, A.; Srinivasan, A. A Review of Some Techniques for Inclusion of Domain-Knowledge into Deep Neural Networks. *Sci. Rep.* **2022**, *12*, 1040. [\[CrossRef\]](#)
13. van den Broek, E.; Sergeeva, A.; Huysman Vrije, M. When the Machine Meets the Expert: An Ethnography of Developing AI for Hiring. *MIS Q.* **2021**, *45*, 1557–1580. [\[CrossRef\]](#)
14. Hwang, G.-J.; Tu, Y.-F. Roles and Research Trends of Artificial Intelligence in Mathematics Education: A Bibliometric Mapping Analysis and Systematic Review. *Mathematics* **2021**, *9*, 584. [\[CrossRef\]](#)
15. Markus, A.F.; Kors, J.A.; Rijnbeek, P.R. The Role of Explainability in Creating Trustworthy Artificial Intelligence for Health Care: A Comprehensive Survey of the Terminology, Design Choices, and Evaluation Strategies. *J. Biomed. Inform.* **2021**, *113*, 103655. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Pan, Y.; Zhang, L. Roles of Artificial Intelligence in Construction Engineering and Management: A Critical Review and Future Trends. *Autom. Constr.* **2021**, *122*, 103517. [\[CrossRef\]](#)
17. Aggarwal, K.; Mijwil, M.M.; Sonia; Al-Mistarehi, A.-H.; Alomari, S.; Gök, M.; Alaabdin, A.M.Z.; Abdulrhman, S.H. Has the Future Started? The Current Growth of Artificial Intelligence, Machine Learning, and Deep Learning. *Iraqi J. Comput. Sci. Math.* **2022**, *3*, 115–123. [\[CrossRef\]](#)
18. Helm, J.M.; Swiergosz, A.M.; Haeberle, H.S.; Karnuta, J.M.; Schaffer, J.L.; Krebs, V.E.; Spitzer, A.I.; Ramkumar, P.N. Machine Learning and Artificial Intelligence: Definitions, Applications, and Future Directions. *Curr. Rev. Musculoskelet. Med.* **2020**, *13*, 69–76. [\[CrossRef\]](#)
19. Xie, X.; Niu, J.; Liu, X.; Chen, Z.; Tang, S.; Yu, S. A Survey on Incorporating Domain Knowledge into Deep Learning for Medical Image Analysis. *Med. Image Anal.* **2021**, *69*, 101985. [\[CrossRef\]](#)
20. O'Brien, H.L.; Kampen, A.; Cole, A.W.; Brennan, K. The Role of Domain Knowledge in Search as Learning. In Proceedings of the 2020 Conference on Human Information Interaction and Retrieval, New York, NY, USA, 14–18 March 2020; pp. 313–317. [\[CrossRef\]](#)
21. Jeong, H.; Kim, J.; Jeong, J.; Kim, H. Deep Learning Models with Stratification-Based Loss Function on Domain Knowledge-Based Time Series Data: Hypotension Prediction. In Proceedings of the 2022 IEEE International Conference on Big Data (Big Data), Osaka, Japan, 17–20 December 2022; pp. 2765–2770. [\[CrossRef\]](#)
22. Kerrigan, D.; Hullman, J.; Bertini, E. A Survey of Domain Knowledge Elicitation in Applied Machine Learning. *Multimodal Technol. Interact.* **2021**, *5*, 73. [\[CrossRef\]](#)
23. Guo, K.; Yang, Z.; Yu, C.-H.; Buehler, M.J. Artificial Intelligence and Machine Learning in Design of Mechanical Materials. *Mater. Horiz.* **2021**, *8*, 1153–1172. [\[CrossRef\]](#)
24. Zhang, F.; Mei, Y.; Nguyen, S.; Zhang, M. Evolving Scheduling Heuristics via Genetic Programming With Feature Selection in Dynamic Flexible Job-Shop Scheduling. *IEEE Trans. Cybern.* **2021**, *51*, 1797–1811. [\[CrossRef\]](#)
25. Sajid, U.; Khan, R.A.; Shah, S.M.; Arif, S. Breast Cancer Classification Using Deep Learned Features Boosted with Handcrafted Features. *Biomed. Signal Process Control* **2023**, *86*, 105353. [\[CrossRef\]](#)
26. Hossain, S.S.; Ebrahimi, M.R.; Padmanabhan, B.; El Naqa, I.; Kuo, P.C.; Beard, A.; Merkel, S. Robust AI-Enabled Simulation of Treatment Paths with Markov Decision Process for Breast Cancer Patients. In Proceedings of the 2023 IEEE Conference on Artificial Intelligence (CAI), Santa Clara, CA, USA, 5–6 June 2023; pp. 105–108. [\[CrossRef\]](#)
27. Duggento, A.; Conti, A.; Mauriello, A.; Guerrisi, M.; Toschi, N. Deep Computational Pathology in Breast Cancer. *Semin. Cancer Biol.* **2021**, *72*, 226–237. [\[CrossRef\]](#)
28. Kyono, T.; Gilbert, F.J.; Schaar, M. Multi-View Multi-Task Learning for Improving Autonomous Mammogram Diagnosis. In Proceedings of the Machine Learning for Healthcare Conference, Ann Arbor, MI, USA, 9–10 August 2019; pp. 571–591.
29. Horváth, D.; Bocsi, K.; Erdős, G.; Istenes, Z. Sim2Real Grasp Pose Estimation for Adaptive Robotic Applications. *IFAC-Pap.* **2023**, *56*, 5233–5239. [\[CrossRef\]](#)
30. Pashevich, A.; Strudel, R.; Kalevatykh, I.; Laptev, I.; Schmid, C. Learning to Augment Synthetic Images for Sim2Real Policy Transfer. In Proceedings of the 2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Macao, China, 4–8 November 2019; pp. 2651–2657. [\[CrossRef\]](#)
31. Rizzardo, C.; Katyara, S.; Fernandes, M.; Chen, F. The Importance and the Limitations of Sim2real for Robotic Manipulation in Precision Agriculture. *arXiv* **2020**, arXiv:2008.03983.
32. Holzinger, A.; Haibe-Kains, B.; Jurisica, I. Why Imaging Data Alone Is Not Enough: AI-Based Integration of Imaging, Omics, and Clinical Data. *Eur. J. Nucl. Med. Mol. Imaging* **2019**, *46*, 2722–2730. [\[CrossRef\]](#) [\[PubMed\]](#)
33. Kovalerchuk, B.; Andonie, R.; Datia, N.; Nazemi, K.; Banissi, E. Visual Knowledge Discovery with Artificial Intelligence: Challenges and Future Directions. In *Integrating Artificial Intelligence and Visualization for Visual Knowledge Discovery*; Springer: Cham, Switzerland, 2022; pp. 1–27. [\[CrossRef\]](#)
34. Gherbi, E.; Khemissa, H.; Bouchouia, M.; Ayrault, M. From Challenges to Opportunities: A Comprehensive Study of AI-Based In-Vehicle Intrusion Detection Systems. In Proceedings of the IEEE Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 6–9 January 2024. [\[CrossRef\]](#)
35. Birhane, A.; Isaac, W.; Prabhakaran, V.; Diaz, M.; Elish, M.C.; Gabriel, I.; Mohamed, S. Power to the People? Opportunities and Challenges for Participatory AI. In Proceedings of the Equity and Access in Algorithms, Mechanisms, and Optimization, New York, NY, USA, 6–9 October 2022; pp. 1–8. [\[CrossRef\]](#)

36. Mylrea, M.; Robinson, N. Artificial Intelligence (AI) Trust Framework and Maturity Model: Applying an Entropy Lens to Improve Security, Privacy, and Ethical AI. *Entropy* **2023**, *25*, 1429. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Weinberg, L. Rethinking Fairness: An Interdisciplinary Survey of Critiques of Hegemonic ML Fairness Approaches. *J. Artif. Intell. Res.* **2022**, *74*, 75–109. [\[CrossRef\]](#)
38. Bhardwaj, V.; Dhaliwal, B.K.; Sarangi, S.K.; Thiyagu, T.M.; Patidar, A.; Pithawa, D. Conversational AI. In *Conversational Artificial Intelligence*; Wiley: Hoboken, NJ, USA, 2024; pp. 435–457. [\[CrossRef\]](#)
39. Lu, S.; Christie, G.A.; Nguyen, T.T.; Freeman, J.D.; Hsu, E.B. Applications of Artificial Intelligence and Machine Learning in Disasters and Public Health Emergencies. *Disaster Med. Public. Health Prep.* **2022**, *16*, 1674–1681. [\[CrossRef\]](#)
40. Dunsin, D.; Ghanem, M.C.; Ouazzane, K.; Vassilev, V. A Comprehensive Analysis of the Role of Artificial Intelligence and Machine Learning in Modern Digital Forensics and Incident Response. *Forensic Sci. Int. Digit. Investig.* **2024**, *48*, 301675. [\[CrossRef\]](#)
41. Zhang, K.; Li, Y.; Wang, J.; Cambria, E.; Li, X. Real-Time Video Emotion Recognition Based on Reinforcement Learning and Domain Knowledge. *IEEE Trans. Circuits Syst. Video Technol.* **2022**, *32*, 1034–1047. [\[CrossRef\]](#)
42. Wolf, C.T. AI Models and Their Worlds: Investigating Data-Driven, AI/ML Ecosystems Through a Work Practices Lens. In *Sustainable Digital Communities, Proceedings of the 15th International Conference, iConference 2020, Borås, Sweden, 23–26 March 2020*; Springer International Publishing: Berlin/Heidelberg, Germany, 2020; pp. 651–664. [\[CrossRef\]](#)
43. Pan, S.L.; Nishant, R. Artificial Intelligence for Digital Sustainability: An Insight into Domain-Specific Research and Future Directions. *Int. J. Inf. Manag.* **2023**, *72*, 102668. [\[CrossRef\]](#)
44. Babushkina, D.; Votsis, A. Epistemo-Ethical Constraints on AI-Human Decision Making for Diagnostic Purposes. *Ethics Inf. Technol.* **2022**, *24*, 22. [\[CrossRef\]](#)
45. Bennett, S.J. *Transmuting Values in Artificial Intelligence: Investigating the Motivations and Contextual Constraints Shaping the Ethics of Artificial Intelligence Practitioners*; The University of Edinburgh: Edinburgh, UK, 2023. [\[CrossRef\]](#)
46. Akkaya, N.; Ünsal, G.; Orhan, K. Understanding of AI in Dental Field with Technical Aspects. In *Artificial Intelligence in Dentistry*; Springer International Publishing: Cham, Switzerland, 2023; pp. 9–31. [\[CrossRef\]](#)
47. Madni, A.M. Augmented Intelligence. In *Systems Engineering for the Digital Age*; Wiley: Hoboken, NJ, USA, 2023; pp. 375–391. [\[CrossRef\]](#)
48. Crisan, A.; Fiore-Gartland, B.; Tory, M. Passing the Data Baton: A Retrospective Analysis on Data Science Work and Workers. *IEEE Trans. Vis. Comput. Graph.* **2021**, *27*, 1860–1870. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Piorkowski, D.; Park, S.; Wang, A.Y.; Wang, D.; Muller, M.; Portnoy, F. How AI Developers Overcome Communication Challenges in a Multidisciplinary Team. *Proc. ACM Hum. Comput. Interact.* **2021**, *5*, 1–25. [\[CrossRef\]](#)
50. Nahar, N.; Zhou, S.; Lewis, G.; Kästner, C. Collaboration Challenges in Building ML-Enabled Systems. In Proceedings of the 44th International Conference on Software Engineering, New York, NY, USA, 21–29 May 2022; pp. 413–425. [\[CrossRef\]](#)
51. Martinez, I.; Viles, E.; Olaizola, I.G. Data Science Methodologies: Current Challenges and Future Approaches. *Big Data Res.* **2021**, *24*, 100183. [\[CrossRef\]](#)
52. Pennington, D.; Ebert-Uphoff, I.; Freed, N.; Martin, J.; Pierce, S.A. Bridging Sustainability Science, Earth Science, and Data Science through Interdisciplinary Education. *Sustain. Sci.* **2020**, *15*, 647–661. [\[CrossRef\]](#)
53. Makinen, S.; Skogstrom, H.; Laaksonen, E.; Mikkonen, T. Who Needs MLOps: What Data Scientists Seek to Accomplish and How Can MLOps Help? In Proceedings of the 2021 IEEE/ACM 1st Workshop on AI Engineering—Software Engineering for AI (WAIN), Madrid, Spain, 30–31 May 2021; pp. 109–112. [\[CrossRef\]](#)
54. Sarker, I.H.; Hoque, M.M.; Uddin, M.K.; Alsanoosy, T. Mobile Data Science and Intelligent Apps: Concepts, AI-Based Modeling and Research Directions. *Mob. Netw. Appl.* **2021**, *26*, 285–303. [\[CrossRef\]](#)
55. Sarker, I.H.; Kayes, A.S.M.; Badsha, S.; Alqahtani, H.; Watters, P.; Ng, A. Cybersecurity Data Science: An Overview from Machine Learning Perspective. *J. Big Data* **2020**, *7*, 41. [\[CrossRef\]](#)
56. Kaur, H.; Nori, H.; Jenkins, S.; Caruana, R.; Wallach, H.; Wortman Vaughan, J. Interpreting Interpretability: Understanding Data Scientists’ Use of Interpretability Tools for Machine Learning. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, New York, NY, USA, 25–30 April 2020; pp. 1–14. [\[CrossRef\]](#)
57. Latif, S.; Usman, M.; Manzoor, S.; Iqbal, W.; Qadir, J.; Tyson, G.; Castro, I.; Razi, A.; Boulos, M.N.K.; Weller, A.; et al. Leveraging Data Science to Combat COVID-19: A Comprehensive Review. *IEEE Trans. Artif. Intell.* **2020**, *1*, 85–103. [\[CrossRef\]](#)
58. Drozdal, J.; Weisz, J.; Wang, D.; Dass, G.; Yao, B.; Zhao, C.; Muller, M.; Ju, L.; Su, H. Trust in AutoML. In Proceedings of the 25th International Conference on Intelligent User Interfaces, New York, NY, USA, 17 March 2020; pp. 297–307.
59. Drosos, I.; Barik, T.; Guo, P.J.; DeLine, R.; Gulwani, S. Wrex: A Unified Programming-by-Example Interaction for Synthesizing Readable Code for Data Scientists. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, New York, NY, USA, 21 April 2020; pp. 1–12.
60. Maier-Hein, L.; Eisenmann, M.; Sarikaya, D.; März, K.; Collins, T.; Malpani, A.; Fallert, J.; Feussner, H.; Giannarou, S.; Mascagni, P.; et al. Surgical Data Science—From Concepts toward Clinical Translation. *Med. Image Anal.* **2022**, *76*, 102306. [\[CrossRef\]](#)
61. Wang, C.; Hu, Q. Knowledge Sharing in Supply Chain Networks: Effects of Collaborative Innovation Activities and Capability on Innovation Performance. *Technovation* **2020**, *94*, 102010. [\[CrossRef\]](#)
62. Shahzad, M.; Qu, Y.; Zafar, A.U.; Appolloni, A. Does the Interaction between the Knowledge Management Process and Sustainable Development Practices Boost Corporate Green Innovation? *Bus. Strategy Environ.* **2021**, *30*, 4206–4222. [\[CrossRef\]](#)

63. Chowdhury, S.; Budhwar, P.; Dey, P.K.; Joel-Edgar, S.; Abadie, A. AI-Employee Collaboration and Business Performance: Integrating Knowledge-Based View, Socio-Technical Systems and Organisational Socialisation Framework. *J. Bus. Res.* **2022**, *144*, 31–49. [\[CrossRef\]](#)
64. Chowdhury, S.; Dey, P.; Joel-Edgar, S.; Bhattacharya, S.; Rodriguez-Espindola, O.; Abadie, A.; Truong, L. Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework. *Human. Resour. Manag. Rev.* **2023**, *33*, 100899. [\[CrossRef\]](#)
65. Kim, J. Leading Teachers' Perspective on Teacher-AI Collaboration in Education. *Educ. Inf. Technol.* **2023**, *29*, 8693–8724. [\[CrossRef\]](#)
66. Sowa, K.; Przegalinska, A.; Ciechanowski, L. Cobots in Knowledge Work. *J. Bus. Res.* **2021**, *125*, 135–142. [\[CrossRef\]](#)
67. Darko, A.; Chan, A.P.C.; Adabre, M.A.; Edwards, D.J.; Hosseini, M.R.; Ameyaw, E.E. Artificial Intelligence in the AEC Industry: Scientometric Analysis and Visualization of Research Activities. *Autom. Constr.* **2020**, *112*, 103081. [\[CrossRef\]](#)
68. Zhang, R.; McNeese, N.J.; Freeman, G.; Musick, G. An Ideal Human. *Proc. ACM Hum. Comput. Interact.* **2021**, *4*, 1–25. [\[CrossRef\]](#)
69. Korteling, J.E. (Hans); van de Boer-Visschedijk, G.C.; Blankendaal, R.A.M.; Boonekamp, R.C.; Eikelboom, A.R. Human- versus Artificial Intelligence. *Front. Artif. Intell.* **2021**, *4*, 622364. [\[CrossRef\]](#)
70. Makarius, E.E.; Mukherjee, D.; Fox, J.D.; Fox, A.K. Rising with the Machines: A Sociotechnical Framework for Bringing Artificial Intelligence into the Organization. *J. Bus. Res.* **2020**, *120*, 262–273. [\[CrossRef\]](#)
71. Allioui, H.; Mourdi, Y. Unleashing the Potential of AI: Investigating Cutting-Edge Technologies That Are Transforming Businesses. *Int. J. Comput. Eng. Data Sci. (IJCEDS)* **2023**, *3*, 1–12.
72. Musick, G.; O'Neill, T.A.; Schelble, B.G.; McNeese, N.J.; Henke, J.B. What Happens When Humans Believe Their Teammate Is an AI? An Investigation into Humans Teaming with Autonomy. *Comput. Human. Behav.* **2021**, *122*, 106852. [\[CrossRef\]](#)
73. Akata, Z.; Balliet, D.; de Rijke, M.; Dignum, F.; Dignum, V.; Eiben, G.; Fokkens, A.; Grossi, D.; Hindriks, K.; Hoos, H.; et al. A Research Agenda for Hybrid Intelligence: Augmenting Human Intellect With Collaborative, Adaptive, Responsible, and Explainable Artificial Intelligence. *Computer* **2020**, *53*, 18–28. [\[CrossRef\]](#)
74. Sjödin, D.; Parida, V.; Palmié, M.; Wincent, J. How AI Capabilities Enable Business Model Innovation: Scaling AI through Co-Evolutionary Processes and Feedback Loops. *J. Bus. Res.* **2021**, *134*, 574–587. [\[CrossRef\]](#)
75. Reim, W.; Åström, J.; Eriksson, O. Implementation of Artificial Intelligence (AI): A Roadmap for Business Model Innovation. *AI* **2020**, *1*, 180–191. [\[CrossRef\]](#)
76. Seo, K.; Tang, J.; Roll, I.; Fels, S.; Yoon, D. The Impact of Artificial Intelligence on Learner–Instructor Interaction in Online Learning. *Int. J. Educ. Technol. High. Educ.* **2021**, *18*, 54. [\[CrossRef\]](#)
77. O'Brien, A.D.; Stone, D.N. Yes, You Can Import, Analyze, and Create Dashboards and Storyboards in Tableau! The GBI Case. *J. Emerg. Technol. Account.* **2020**, *17*, 21–31. [\[CrossRef\]](#)
78. Kharakhash, O. Data Visualization: Transforming Complex Data into Actionable Insights. *Autom. Technol. Bus. Process.* **2023**, *15*, 4–12. [\[CrossRef\]](#)
79. Paff, J.B. *Cognitive Feedback Theories and Artificial Intelligence: A Case for A Grammarly of UI/UX Design*; Dartmouth College: Hanover, NH, USA, 2023.
80. Wu, Y.; Hellerstein, J.M.; Satyanarayan, A. B2: Bridging Code and Interactive Visualization in Computational Notebooks. In Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology, New York, NY, USA, 20 October 2020; pp. 152–165.
81. Kelly, T.D.; Foster, T. AquaCrop-OSPy: Bridging the Gap between Research and Practice in Crop-Water Modeling. *Agric. Water Manag.* **2021**, *254*, 106976. [\[CrossRef\]](#)
82. Grotov, K.; Titov, S.; Sotnikov, V.; Golubev, Y.; Bryksin, T. A Large-Scale Comparison of Python Code in Jupyter Notebooks and Scripts. In Proceedings of the 19th International Conference on Mining Software Repositories, New York, NY, USA, 17 October 2022; pp. 353–364. [\[CrossRef\]](#)
83. Sadreddin, A.; Chan, Y.E. Pathways to Developing Information Technology-Enabled Capabilities in Born-Digital New Ventures. *Int. J. Inf. Manag.* **2023**, *68*, 102572. [\[CrossRef\]](#)
84. Integlia, R.; Chatterjee, P.; Gilmore, J. Collaborative Course Development for Applications of Artificial Intelligence and Wearable Devices in Healthcare. In Proceedings of the 2022 ASEE Southeast Section Conference, Charleston, CA, USA, 13–15 March 2022.
85. Martelaro, N.; Myers, B.A. UX Design Tools. In *User Experience Methods and Tools in Human-Computer Interaction*; CRC Press: Boca Raton, FL, USA, 2024; pp. 350–372.
86. Hsiao, H.-L.; Tang, H.-H. A Study on the Application of Generative AI Tools in Assisting the User Experience Design Process. In Proceedings of the International Conference on Human-Computer Interaction, Washington, DC, USA, 29 June–4 July 2024; pp. 175–189. [\[CrossRef\]](#)
87. Jiang, Y.; Lu, Y.; Kliman-Silver, C.; Lutteroth, C.; Li, T.J.-J.; Nichols, J.; Stuerzlinger, W. Computational Methodologies for Understanding, Automating, and Evaluating User Interfaces. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*; Association for Computing Machinery: New York, NY, USA, 2023. [\[CrossRef\]](#)
88. Heo, J.; Lee, U. Form to Flow: Exploring Challenges and Roles of Conversational UX Designers in Real-World, Multi-Channel Service Environments. *Proc. ACM Hum. Comput. Interact.* **2023**, *7*, 1–24. [\[CrossRef\]](#)
89. Medeiros, D.; Schieffer, G.; Wahlgren, J.; Peng, I. A GPU-Accelerated Molecular Docking Workflow with Kubernetes and Apache Airflow. In *International Conference on High Performance Computing*; Springer Nature Switzerland: Cham, Switzerland, 2023; pp. 193–206. [\[CrossRef\]](#)

90. Saxena, R. Big Data in Construction Perspective: Exploration of Google Cloud Based Technologies and Offerings. *Lond. J. Eng. Res.* **2023**, *23*, 25–43.
91. Abdeldayem, O.M.; Dabbish, A.M.; Habashy, M.M.; Mostafa, M.K.; Elhefnawy, M.; Amin, L.; Al-Sakkari, E.G.; Ragab, A.; Rene, E.R. Viral Outbreaks Detection and Surveillance Using Wastewater-Based Epidemiology, Viral Air Sampling, and Machine Learning Techniques: A Comprehensive Review and Outlook. *Sci. Total Environ.* **2022**, *803*, 149834. [\[CrossRef\]](#) [\[PubMed\]](#)
92. Shipley, E.; Joddrell, M.; Lip, G.Y.; Zheng, Y. Bridging the Gap Between Artificial Intelligence Research and Clinical Practice in Cardiovascular Science: What the Clinician Needs to Know. *Arrhythm. Electrophysiol. Rev.* **2022**, *11*, e03. [\[CrossRef\]](#) [\[PubMed\]](#)
93. Tucker, J.; Haley, J.; Kessler, B.; Fish, T. Bridging the Gap from Academia to Application: Rapid Algorithm Design and Deployment for Artificial Intelligence. In *Artificial Intelligence and Machine Learning in Defense Applications III*; Dijk, J., Ed.; SPIE: Bellingham, WA, USA, 2021; p. 8. [\[CrossRef\]](#)
94. Krishnam, N.P.; Ashraf, M.S.; Rajagopal, B.R.; Vats, P.; Chakravarthy, D.S.K.; Rafi, S.M. Analysis Of Current Trends, Advances And Challenges Of Machine Learning (ML) And Knowledge Extraction: From ML To Explainable AI. *Ind. Qualif. Inst. Adm. Manag. UK* **2022**, *58*, 54–62.
95. Shao, S.; Henrique Ribeiro, P.; Ramirez, C.M.; Moore, J.H. A Review of Feature Selection Strategies Utilizing Graph Data Structures and Knowledge Graphs. *Brief. Bioinform.* **2024**, *25*, bbae521. [\[CrossRef\]](#)
96. Bala, B.; Behal, S. A Brief Survey of Data Preprocessing in Machine Learning and Deep Learning Techniques. In Proceedings of the 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Kathmandu, Nepal, 3–5 October 2024; pp. 1755–1762. [\[CrossRef\]](#)
97. Rout, S.; Mallick, R.; Kumar Sahu, S. Exploring the Significance of Feature Analysis in AI/ML Modeling. In Proceedings of the 2023 OITS International Conference on Information Technology (OCIT), Raipur, India, 13–15 December 2023; pp. 580–585. [\[CrossRef\]](#)
98. Oetli, F.C.; Oeding, J.F.; Feldt, R.; Ley, C.; Hirschmann, M.T.; Samuelsson, K. The Artificial Intelligence Advantage: Supercharging Exploratory Data Analysis. *Knee Surg. Sports Traumatol. Arthrosc.* **2024**, *32*, 3039–3042. [\[CrossRef\]](#)
99. Milo, T.; Somech, A. Automating Exploratory Data Analysis via Machine Learning: An Overview. In Proceedings of the 2020 ACM SIGMOD International Conference on Management of Data, New York, NY, USA, 14–19 June 2020; pp. 2617–2622. [\[CrossRef\]](#)
100. Holstein, J. Bridging Domain Expertise and AI through Data Understanding. In Proceedings of the 29th International Conference on Intelligent User Interfaces, New York, NY, USA, 18–21 March 2024; pp. 163–165. [\[CrossRef\]](#)
101. Nazary, F.; Deldjoo, Y.; Di Noia, T. ChatGPT-HealthPrompt. Harnessing the Power of XAI in Prompt-Based Healthcare Decision Support Using ChatGPT. In Proceedings of the Artificial Intelligence. ECAI 2023 International Workshops, Kraków, Poland, 30 September–4 October 2024; pp. 382–397. [\[CrossRef\]](#)
102. Wu, T.-H.; Kao, B.; Cheung, A.S.Y.; Cheung, M.M.K.; Wang, C.; Chen, Y.; Yuan, G.; Cheng, R. Integrating Domain Knowledge in AI-Assisted Criminal Sentencing of Drug Trafficking Cases. In *Legal Knowledge and Information Systems*; IOS Press: Amsterdam, The Netherlands, 2020. [\[CrossRef\]](#)
103. Tasnim, N.; Al Mamun, S.; Islam, M.S.; Kaiser, M.S.; Mahmud, M. Explainable Mortality Prediction Model for Congestive Heart Failure with Nature-Based Feature Selection Method. *Appl. Sci.* **2023**, *13*, 6138. [\[CrossRef\]](#)
104. Feustel, I.; Rach, N.; Minker, W.; Ultes, S. Enhancing Model Transparency: A Dialogue System Approach to XAI with Domain Knowledge. In Proceedings of the 25th Annual Meeting of the Special Interest Group on Discourse and Dialogue; Association for Computational Linguistics: Stroudsburg, PA, USA, 2024; pp. 248–258. [\[CrossRef\]](#)
105. Ignatiev, A.; Marques-Silva, J.; Narodytska, N.; Stuckey, P.J. Reasoning-Based Learning of Interpretable ML Models. In *IJCAI International Joint Conference on Artificial Intelligence, Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, Virtual, MO, Canada, 30 August 2021*; International Joint Conferences on Artificial Intelligence Organization: Marina del Rey, CA, USA, 2021; pp. 4458–4465. [\[CrossRef\]](#)
106. Sahoo, P.; Singh, A.K.; Saha, S.; Jain, V.; Mondal, S.; Chadha, A. A Systematic Survey of Prompt Engineering in Large Language Models: Techniques and Applications. *arXiv* **2024**, arXiv:2402.07927.
107. Chen, E.; Wang, D.; Xu, L.; Cao, C.; Fang, X.; Lin, J. A Systematic Review on Prompt Engineering in Large Language Models for K-12 STEM Education. *arXiv* **2024**, arXiv:2410.11123.
108. Wang, Z.J.; Chakravarthy, A.; Munechika, D.; Chau, D.H. Wordflow: Social Prompt Engineering for Large Language Models. *arXiv* **2024**, arXiv:2401.14447.
109. Chen, X.; Zeng, Y.; Kang, S.; Jin, R. INN: An Interpretable Neural Network for AI Incubation in Manufacturing. *ACM Trans. Intell. Syst. Technol.* **2022**, *13*, 1–23. [\[CrossRef\]](#)
110. Babic, B.; Gerke, S.; Evgeniou, T.; Cohen, I.G. Algorithms on Regulatory Lockdown in Medicine. *Science* **2019**, *366*, 1202–1204. [\[CrossRef\]](#) [\[PubMed\]](#)
111. Slihte, A.; Osis, J.; Donins, U. Knowledge Integration for Domain Modeling. In Proceedings of the International Workshop on Model-Driven Architecture and Modeling-Driven Software Development, Oldenburg, Germany, 1 March 2011; pp. 46–56.
112. Hall, O.; Ohlsson, M.; Rögnvaldsson, T. Satellite Image and Machine Learning Based Knowledge Extraction in the Poverty and Welfare Domain. *arXiv* **2022**, arXiv:2203.01068. [\[CrossRef\]](#)
113. Chen, X.; Singh, M.M.; Geyer, P. Utilizing Domain Knowledge: Robust Machine Learning for Building Energy Prediction with Small, Inconsistent Datasets. *arXiv* **2023**, arXiv:2302.10784. [\[CrossRef\]](#)

114. Grenaderova, A.V.; Mikhailova, A.B.; Sharafutdinov, R.A.; Stoyko, T.G. Holocene Environmental Conditions in the Eastern Sayan Foothills According to a Comprehensive Paleocological Study of the Sosnovka Mire. *Limnol. Freshw. Biol.* **2024**, *7*, 394–399. [\[CrossRef\]](#)
115. Innocenti, B.; Bori, E.; Pianigiani, S. Biomechanical Analysis of the Use of Stems in Revision Total Knee Arthroplasty. *Bioengineering* **2022**, *9*, 259. [\[CrossRef\]](#)
116. Yang, J.; Ren, S. A Quantitative Perspective on Values of Domain Knowledge for Machine Learning. *arXiv* **2020**, arXiv:2011.08450.
117. Childs, C.M.; Washburn, N.R. Embedding Domain Knowledge for Machine Learning of Complex Material Systems. *MRS Commun.* **2019**, *9*, 806–820. [\[CrossRef\]](#)
118. Constance Obiuto, N.; Adekola Adebayo, R.; Kayode Olajiga, O.; Clinton Festus-Ikhuoria, I. Integrating Artificial Intelligence in Construction Management: Improving Project Efficiency and Cost-Effectiveness. *Int. J. Adv. Multidiscip. Res. Stud.* **2024**, *4*, 639–647. [\[CrossRef\]](#)
119. Termine. *Urologe* **2015**, *54*, 1853–1860. [\[CrossRef\]](#)
120. Schaekermann, M.; Spitz, T.; Pyles, M.; Cole-Lewis, H.; Wulczyn, E.; Pfohl, S.R.; Martin, D.; Jaroensri, R.; Keeling, G.; Liu, Y.; et al. Health Equity Assessment of Machine Learning Performance (HEAL): A Framework and Dermatology AI Model Case Study. *EClinicalMedicine* **2024**, *70*, 102479. [\[CrossRef\]](#) [\[PubMed\]](#)
121. Kumari S AI-Enhanced Portfolio Management: Leveraging Machine Learning for Optimized Investment Strategies in 2024. *J. Inform. Educ. Res.* **2024**, *4*, 1487. [\[CrossRef\]](#)
122. Adelakun, B.O.; Onwubuariri, E.R.; Adeniran, G.A.; Ntiakoh, A. Enhancing Fraud Detection in Accounting through AI: Techniques and Case Studies. *Financ. Account. Res. J.* **2024**, *6*, 978–999. [\[CrossRef\]](#)
123. Han, M. Research on Enhancing Human-Machine Interaction in Medical Exoskeleton Devices through the Integration of Artificial Intelligence. *Appl. Comput. Eng.* **2024**, *71*, 206–211. [\[CrossRef\]](#)
124. Yu, T.; Simoff, S.; Jan, T. VQSVM: A Case Study for Incorporating Prior Domain Knowledge into Inductive Machine Learning. *Neurocomputing* **2010**, *73*, 2614–2623. [\[CrossRef\]](#)
125. Kumar, P.; Chauhan, S.; Awasthi, L.K. Artificial Intelligence in Healthcare: Review, Ethics, Trust Challenges & Future Research Directions. *Eng. Appl. Artif. Intell.* **2023**, *120*, 105894. [\[CrossRef\]](#)
126. Khan, B.; Fatima, H.; Qureshi, A.; Kumar, S.; Hanan, A.; Hussain, J.; Abdullah, S. Drawbacks of Artificial Intelligence and Their Potential Solutions in the Healthcare Sector. *Biomed. Mater. Devices* **2023**, *1*, 731–738. [\[CrossRef\]](#)
127. Baumgartner, R.; Arora, P.; Bath, C.; Burljaev, D.; Ciereszko, K.; Custers, B.; Ding, J.; Ernst, W.; Fosch-Villaronga, E.; Galanos, V.; et al. Fair and Equitable AI in Biomedical Research and Healthcare: Social Science Perspectives. *Artif. Intell. Med.* **2023**, *144*, 102658. [\[CrossRef\]](#)
128. Ueda, D.; Kakinuma, T.; Fujita, S.; Kamagata, K.; Fushimi, Y.; Ito, R.; Matsui, Y.; Nozaki, T.; Nakaura, T.; Fujima, N.; et al. Fairness of Artificial Intelligence in Healthcare: Review and Recommendations. *Jpn. J. Radiol.* **2024**, *42*, 3–15. [\[CrossRef\]](#)
129. Assadi, A.; Laussen, P.C.; Goodwin, A.J.; Goodfellow, S.; Dixon, W.; Greer, R.W.; Jegatheeswaran, A.; Singh, D.; McCradden, M.; Gallant, S.N.; et al. An Integration Engineering Framework for Machine Learning in Healthcare. *Front. Digit. Health* **2022**, *4*, 932411. [\[CrossRef\]](#)
130. Ahmad, M.A.; Patel, A.; Eckert, C.; Kumar, V.; Teredesai, A. Fairness in Machine Learning for Healthcare. In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, New York, NY, USA, 6–10 July 2020; pp. 3529–3530. [\[CrossRef\]](#)
131. Bhowmick, A.; Roy, U. *Inventory Management at Ford Using AI/ML Techniques Considering Demand Forecasting*; Indian Institute of Management Bangalore: Bengaluru, India, 2022.
132. Gupta, A.; ReenaPoojara, D. Diffusion of Artificial Intelligence in Human Resource Domain with Specific Reference to Recruitment Function: A Literature Review Study. *Int. J. Innov. Sci. Res. Technol.* **2022**, *7*, 771–778.
133. Siddiqui, F.; Khan, R.; Sezer, S. Bird’s-Eye View on the Automotive Cybersecurity Landscape & Challenges in Adopting AI/ML. In Proceedings of the 2021 Sixth International Conference on Fog and Mobile Edge Computing (FMEC), Gandia, Spain, 6–9 December 2021; pp. 1–6. [\[CrossRef\]](#)
134. Sukel, K. Brawn with Brains. *Mech. Eng.* **2021**, *143*, 28–31. [\[CrossRef\]](#)
135. Romero-Brufau, S.; Wyatt, K.D.; Boyum, P.; Mickelson, M.; Moore, M.; Cognetta-Rieke, C. A Lesson in Implementation: A Pre-Post Study of Providers’ Experience with Artificial Intelligence-Based Clinical Decision Support. *Int. J. Med. Inform.* **2020**, *137*, 104072. [\[CrossRef\]](#) [\[PubMed\]](#)
136. Giordano, C.; Brennan, M.; Mohamed, B.; Rashidi, P.; Modave, F.; Tighe, P. Accessing Artificial Intelligence for Clinical Decision-Making. *Front. Digit. Health* **2021**, *3*, 645232. [\[CrossRef\]](#) [\[PubMed\]](#)
137. El Naqa, I.; Karolak, A.; Luo, Y.; Folio, L.; Tarhini, A.A.; Rollison, D.; Parodi, K. Translation of AI into Oncology Clinical Practice. *Oncogene* **2023**, *42*, 3089–3097. [\[CrossRef\]](#)
138. Safdar, N.M.; Banja, J.D.; Meltzer, C.C. Ethical Considerations in Artificial Intelligence. *Eur. J. Radiol.* **2020**, *122*, 108768. [\[CrossRef\]](#)
139. Cheng, L.; Varshney, K.R.; Liu, H. Socially Responsible AI Algorithms: Issues, Purposes, and Challenges. *J. Artif. Intell. Res.* **2021**, *71*, 1137–1181. [\[CrossRef\]](#)
140. Sanderson, C.; Douglas, D.; Lu, Q.; Schleiger, E.; Whittle, J.; Lacey, J.; Newnham, G.; Hajkowicz, S.; Robinson, C.; Hansen, D. AI Ethics Principles in Practice: Perspectives of Designers and Developers. *IEEE Trans. Technol. Soc.* **2023**, *4*, 171–187. [\[CrossRef\]](#)

141. Pant, A.; Hoda, R.; Spiegler, S.V.; Tantithamthavorn, C.; Turhan, B. Ethics in the Age of AI: An Analysis of AI Practitioners' Awareness and Challenges. *ACM Trans. Softw. Eng. Methodol.* **2023**, *33*, 1–35. [\[CrossRef\]](#)
142. Lo Piano, S. Ethical Principles in Machine Learning and Artificial Intelligence: Cases from the Field and Possible Ways Forward. *Humanit. Soc. Sci. Commun.* **2020**, *7*, 9. [\[CrossRef\]](#)
143. Garrett, N.; Beard, N.; Fiesler, C. More Than “If Time Allows”. In Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, New York, NY, USA, 7–8 February 2020; pp. 272–278. [\[CrossRef\]](#)
144. Fletcher, R.R.; Nakeshimana, A.; Olubeko, O. Addressing Fairness, Bias, and Appropriate Use of Artificial Intelligence and Machine Learning in Global Health. *Front. Artif. Intell.* **2021**, *3*, 561802. [\[CrossRef\]](#) [\[PubMed\]](#)
145. Abràmoff, M.D.; Tarver, M.E.; Loyo-Berrios, N.; Trujillo, S.; Char, D.; Obermeyer, Z.; Eydelman, M.B.; Maisel, W.H. Considerations for Addressing Bias in Artificial Intelligence for Health Equity. *NPJ Digit. Med.* **2023**, *6*, 170. [\[CrossRef\]](#) [\[PubMed\]](#)
146. Mehrabi, N.; Morstatter, F.; Saxena, N.; Lerman, K.; Galstyan, A. A Survey on Bias and Fairness in Machine Learning. *ACM Comput. Surv.* **2022**, *54*, 1–35. [\[CrossRef\]](#)
147. Carter, S.M.; Rogers, W.; Win, K.T.; Frazer, H.; Richards, B.; Houssami, N. The Ethical, Legal and Social Implications of Using Artificial Intelligence Systems in Breast Cancer Care. *Breast* **2020**, *49*, 25–32. [\[CrossRef\]](#)
148. Taeihagh, A. Governance of Artificial Intelligence. *Policy Soc.* **2021**, *40*, 137–157. [\[CrossRef\]](#)
149. Robles Carrillo, M. Artificial Intelligence: From Ethics to Law. *Telecomm Policy* **2020**, *44*, 101937. [\[CrossRef\]](#)
150. Chesterman, S. Artificial Intelligence and The Limits of Legal Personality. *Int. Comp. Law. Q.* **2020**, *69*, 819–844. [\[CrossRef\]](#)
151. Sun, A.Y.; Yoon, H.; Shih, C.-Y.; Zhong, Z. Applications of Physics-Informed Scientific Machine Learning in Subsurface Science: A Survey. In *Knowledge Guided Machine Learning*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2022; pp. 111–132.
152. Borders, T.; Glenski, M.; Grimes, T.; Mendez, J.; Seiner, B.; Sheffield, A.; Shields, A.; Ward, J.; Wonders, M. *Report on Next-Gen AI for Proliferation Detection Workshop: Domain-Aware Methods*; Pacific Northwest National Laboratory: Richland, WA, USA, 2021.
153. Freeman, L.; Rahman, A.; Batarseh, F.A. Enabling Artificial Intelligence Adoption through Assurance. *Soc. Sci.* **2021**, *10*, 322. [\[CrossRef\]](#)
154. Brockman Shields, A.J. *Domain Aware Techniques in AI: A Survey*; Idaho National Lab. (INL): Idaho Falls, ID, USA, 2021.
155. Jia, Z.; Chen, J.; Xu, X.; Kheir, J.; Hu, J.; Xiao, H.; Peng, S.; Hu, X.S.; Chen, D.; Shi, Y. The Importance of Resource Awareness in Artificial Intelligence for Healthcare. *Nat. Mach. Intell.* **2023**, *5*, 687–698. [\[CrossRef\]](#)
156. Brea, E.; Ford, J.A. Innovative Problem Solving in the Machine Learning Age: Is Domain Expertise Still Important? *Acad. Manag. Proc.* **2023**, *2023*, 14780. [\[CrossRef\]](#)
157. She, C.; Sun, C.; Gu, Z.; Li, Y.; Yang, C.; Poor, H.V.; Vucetic, B. A Tutorial on Ultrareliable and Low-Latency Communications in 6G: Integrating Domain Knowledge Into Deep Learning. *Proc. IEEE* **2021**, *109*, 204–246. [\[CrossRef\]](#)
158. Deng, C.; Ji, X.; Rainey, C.; Zhang, J.; Lu, W. Integrating Machine Learning with Human Knowledge. *iScience* **2020**, *23*, 101656. [\[CrossRef\]](#) [\[PubMed\]](#)
159. Luo, X.; Zhang, D.; Zhu, X. Deep Learning Based Forecasting of Photovoltaic Power Generation by Incorporating Domain Knowledge. *Energy* **2021**, *225*, 120240. [\[CrossRef\]](#)
160. Sambasivan, N.; Veeraraghavan, R. The Deskilling of Domain Expertise in AI Development. In Proceedings of the CHI Conference on Human Factors in Computing Systems, New York, NY, USA, 29 April 2022; pp. 1–14. [\[CrossRef\]](#)
161. Biagini, V.; Subasic, M.; Oudalov, A.; Kreusel, J. The Autonomous Grid: Automation, Intelligence and the Future of Power Systems. *Energy Res. Soc. Sci.* **2020**, *65*, 101460. [\[CrossRef\]](#)
162. Parashar, G.; Chaudhary, A.; Rana, A. Systematic Mapping Study of AI/Machine Learning in Healthcare and Future Directions. *SN Comput. Sci.* **2021**, *2*, 461. [\[CrossRef\]](#)
163. Kumari, M.; Chaudhary, A.; Narayan, Y. *Explainable AI (XAI): A Survey of Current and Future Opportunities*; Springer International Publishing: Cham, Switzerland, 2023; pp. 53–71. [\[CrossRef\]](#)
164. Gertrude, M.; Kati, R.; Masibo, E. Comparative Analysis of Assessment Methods Enabled by Learning Management System in Technical Training Institutions in Kenya. *J. Educ. Pract.* **2024**, *15*, 51–64. [\[CrossRef\]](#)

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