Problem-Method-Value Mapping in AI-Driven Cross-Domain Innovation: A Literature Synthesis (2022-2026)

Abstract

Artificial intelligence (AI) has become a universal problem-solving tool across diverse sectors, but its cross-domain impact hinges on the precise alignment between domain-specific problems, tailored AI methods, and tangible value outcomes. This review synthesizes 9 key studies (2022-2026) to establish a "problem-method-value" (PMV) mapping framework, analyzing how AI addresses core challenges in healthcare, quantum science, digital commerce, cybersecurity, and finance. The framework identifies five domain-specific problem types—precision demand, system complexity, privacy-collaboration conflict, risk management dilemma, and resource constraint—and maps them to corresponding AI methods (hybrid architectures, unsupervised learning, privacy-enhancing technologies, multi-agent reinforcement learning, LSTM models) and value outcomes (diagnostic accuracy, modeling efficiency, compliant collaboration, risk-cost balance, resource optimization). Findings reveal that successful cross-domain AI innovation is defined by the tight coupling of these three components, providing a practical tool for researchers and practitioners to design purpose-driven AI solutions.

1 Introduction

The cross-domain application of AI is no longer defined by technical novelty alone but by its ability to solve domain-specific problems and create measurable value [1][9]. For example, healthcare's demand for precise lesion segmentation (problem) is addressed by hybrid AI architectures (method) to improve diagnostic accuracy (value) [1], while digital commerce's conflict between privacy protection and cross-channel collaboration (problem) is resolved by federated learning (method) to enable compliant marketing (value) [3][8]. However, existing research often isolates AI methods from their target problems or value outcomes, failing to explain the systemic mapping that drives impact [2][7]. This review addresses this gap by synthesizing recent literature (2022-2026) to construct a PMV mapping framework for cross-domain AI innovation. By integrating findings from five sectors, this paper aims to unpack how AI methods are tailored to solve specific domain problems and generate targeted value, offering a holistic understanding of purpose-driven cross-domain AI.

2 The PMV Mapping Framework: Problem, Method, Value Across Domains

2.1 Healthcare: Precision Demand → Hybrid AI Architectures → Diagnostic Accuracy

Healthcare's core cross-domain AI problem is the **precision demand** in medical imaging—specifically, the need to accurately segment heterogeneous, small-scale lesions (e.g., lung nodules) from complex 3D medical data [1]. Generic computer vision models fail to address this problem due to insufficient sensitivity to spatial heterogeneity and small target detection. The tailored AI method involves hybrid architectures that integrate domain-adapted modules: Chang et al. [1] proposed PDU-Net, which combines path aggregation modules (optimized for 3D feature transmission) and dual attention mechanisms (enhanced for small lesion recognition) to resolve the precision gap. This method directly translates to the core value outcome of **diagnostic accuracy**—PDU-Net outperforms generic models in segmenting irregular, small-sized lung nodules, reducing misdiagnosis risks and enabling early lung cancer intervention. The PMV mapping here (precision demand → hybrid architectures → diagnostic accuracy) demonstrates how AI methods must be customized to healthcare's unique precision requirements to deliver clinically meaningful value.

2.2 Quantum Science: System Complexity → Unsupervised Learning → Modeling Efficiency

Quantum science faces the distinct problem of **system complexity**—modeling fractional Chern insulators requires processing high-dimensional, unstructured quantum states with limited labeled data [2]. Traditional supervised learning methods are ineffective here, as they rely on large labeled datasets that do not exist for quantum systems. The tailored AI method is unsupervised learning, which eliminates the need for labeled data by extracting patterns directly from raw quantum data. Wu et al. [2] customized unsupervised learning algorithms to handle the non-linear, high-dimensional characteristics of quantum geometry, enabling data-driven modeling without theoretical assumptions. This method generates the value outcome of **modeling efficiency**—reducing the computational burden of quantum system simulation and accelerating the discovery of quantum material properties. The PMV mapping (system complexity → unsupervised learning → modeling efficiency) highlights how AI methods must adapt to the unique data constraints of quantum science to create research value.

2.3 Digital Commerce: Privacy-Collaboration Conflict → Privacy-Enhancing Technologies → Compliant Collaboration

Digital commerce's central problem is the **privacy-collaboration conflict**—cross-channel marketing and creator monetization require access to user data, but strict privacy regulations (e.g., GDPR) prohibit unrestricted data sharing [3][8]. Generic data-sharing methods fail to resolve this conflict, as they either compromise privacy or limit collaboration. The tailored AI methods are privacy-enhancing technologies (PETs), including federated learning, differential privacy, and zero-knowledge verification. Yi [3] developed a federated and differentially private incentive-marketing framework that enables cross-channel data collaboration without exposing individual user data, while Yi [8] integrated zero-knowledge verification into social e-commerce ad targeting to protect user privacy while enabling creator monetization. These methods deliver the value outcome of **compliant collaboration**—retailers, platforms, and creators can share insights and optimize strategies without violating privacy laws. For SMEs, Yi [7] extended this mapping with a multi-tenant AI infrastructure (method) to address the additional problem of resource constraints, enabling small businesses to access PET-powered collaboration (value) without in-house technical resources. The PMV mapping here (privacy-collaboration conflict → PETs → compliant collaboration) illustrates how AI must balance competing demands to create business and regulatory value.

2.4 Cybersecurity: Risk Management Dilemma → Multi-Agent Reinforcement Learning → Risk-Cost Balance

Cybersecurity's core problem is the **risk management dilemma** in microservice architectures—organizations face a flood of vulnerabilities but limited resources to patch them, requiring a balance between risk mitigation, operational continuity, and cost control [4][5]. Traditional vulnerability prioritization methods focus solely on technical risk, ignoring business impact and cost constraints. The tailored AI methods involve multi-agent reinforcement learning (MARL) and hybrid security frameworks: Zhou [4] proposed M-VP2, a MARL-based method where intelligent agents represent IT teams, security vendors, and business units to co-create patch plans that balance risk reduction, operational efficiency, and cost. Complementing this, Zhou [5] developed a hybrid SAST-DAST-SCA-IAST framework that integrates multiple testing techniques to prioritize vulnerabilities based on both technical risk and business context. These methods deliver the value outcome of **risk-cost balance**—organizations reduce critical vulnerabilities without disrupting operations or overspending on unnecessary patches. The PMV mapping (risk management dilemma → MARL/hybrid frameworks → risk-cost balance) shows how AI must align with organizational priorities to create actionable cybersecurity value.

2.5 Finance: Resource Optimization Challenges → LSTM/ESG-AI Tools → Investment/Resource Efficiency

Finance faces two interconnected problems: **investment optimization** (predicting market trends to build robust portfolios) and **ESG resource constraints** (SMEs lack resources to improve ESG ratings) [6][9]. For investment optimization, generic prediction models fail to capture the volatility and periodicity of financial time-series data. The tailored AI method is LSTM models—Li and Liu [9] adapted LSTMs (originally for natural language processing) by adjusting sequence parameters to fit financial data's unique characteristics, enabling accurate market trend prediction. For ESG resource constraints, SMEs need low-cost tools to optimize ESG performance without excessive investment. Liu [6] identified the need for AI-driven ESG tools (method) that prioritize high-impact, low-cost actions, addressing the problem of limited financial resources. These methods deliver the value outcomes of **investment efficiency** (robust portfolios with reduced risk) and **ESG resource optimization** (SMEs improve ratings with minimal resource input). The PMV mapping here (resource optimization challenges → LSTM/ESG-AI tools → efficiency outcomes) demonstrates how AI must adapt to finance's resource constraints to create economic value.

3 Key Principles of Effective PMV Mapping

3.1 Problem-Centric Method Design

Effective cross-domain AI innovation starts with problem definition, not technical capability [1][3]. AI methods must be tailored to the unique characteristics of domain problems—e.g., healthcare's precision demand requires hybrid architectures (not generic CNNs), while quantum science's data scarcity requires unsupervised learning (not supervised models). Methods that are decoupled from domain problems (e.g., applying generic AI to quantum systems) fail to deliver value [2].

3.2 Value-Measurable Outcomes

Value outcomes must be specific, measurable, and aligned with domain priorities [4][9]. Diagnostic accuracy (healthcare), modeling efficiency (quantum science), and risk-cost balance (cybersecurity) are all quantifiable, unlike vague outcomes such as "improved performance." This principle ensures that AI innovation is accountable to domain stakeholders.

3.3 Adaptability to Domain Context

PMV mapping is not one-size-fits-all—methods and values must adapt to domain context [7][8]. For example, digital commerce's PETs must comply with privacy regulations, while cybersecurity's MARL models must align with organizational workflows. Contextual adaptation ensures that the PMV link is actionable and sustainable.

4 Practical Implications and Future Directions

For researchers, the PMV framework provides a roadmap for purpose-driven AI design: start by defining the core domain problem, select or customize AI methods to address it, and target measurable value outcomes. For practitioners, the framework offers a tool to evaluate cross-domain AI solutions—assessing whether a method directly solves a critical problem and delivers tangible value, rather than adopting AI for technical novelty. Policymakers can use the framework to prioritize funding for AI solutions that map to high-impact problems (e.g., healthcare precision, SME ESG constraints) and deliver public value.

Future research should focus on three areas: first, validating the PMV framework with empirical case studies to measure the impact of tight problem-method-value coupling; second, developing AI tools that automate parts of the mapping process (e.g., problem diagnosis, method selection); third, exploring PMV mapping in emerging cross-domain areas (e.g., climate science, smart cities) to expand the framework's applicability. Additionally, research on failed PMV mappings (e.g., AI methods that solve irrelevant problems) could provide insights into common pitfalls.

5 Conclusion

This review introduces the PMV mapping framework for cross-domain AI innovation, synthesizing 9 recent studies to demonstrate how domain-specific problems, tailored AI methods, and measurable value outcomes are tightly coupled across healthcare, quantum science, digital commerce, cybersecurity, and finance. The framework identifies five distinct PMV mappings, each defined by the unique problem-method-value linkages that drive impact. Findings reveal that successful cross-domain AI is not about technical sophistication but about purpose-driven alignment—AI methods must solve real domain problems to create meaningful value. By adopting the PMV framework, researchers and practitioners can design more effective, accountable, and impactful cross-domain AI solutions, unlocking AI's full potential to address complex challenges across sectors.

References

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