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A Review of Master Data Management Technologies and Their Applications Across Diverse Industry Domains

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ABSTRACT

This review explores Master Data Management (MDM) technologies and their applications across multiple industries. Although MDM is vital for achieving unified and reliable data, existing studies lack an integrated cross-sectoral analysis connecting emerging technologies with key MDM components and implementation results. To bridge this gap, a structured literature review was conducted using Snyder's (2019) methodology. Peer-reviewed articles from 2021–2025 were sourced mainly from Scopus, resulting in 43 relevant studies selected from 101 initial records. The analysis, guided by the DAMA-DMBOK framework, reveals growing adoption of AI, machine learning, blockchain, and semantic knowledge graphs in sectors such as healthcare, manufacturing, energy, government, retail, and transportation. Findings show that MDM enhances data quality, governance, and operational efficiency while facing challenges like integration complexity, scalability, and compliance. The review contributes a conceptual framework linking MDM components, enabling technologies, and strategic outcomes to support both research and real-world implementation.

1. INTRODUCTION

Master Data Management is a vital discipline in modern organisations, ensuring a unified, accurate, and consistent representation of core enterprise data. The increasing reliance on digital transformation, combined with the rapid growth of enterprise data, has intensified the need for structured data governance and master data frameworks (Khatri & Brown, 2010; Otto, 2011). As organisations pursue data-driven strategies, Master Data Management plays a critical role in maintaining enterprise-wide consistency, accuracy, and compliance (Weber et al., 2009). Moreover, the expansion of advanced analytics, artificial

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intelligence (AI), and regulatory requirements such as the General Data Protection Regulation (GDPR) further emphasise the importance of developing robust Master Data Management systems that consider both technical and organisational factors (Silvola et al., 2011). According to Singh and Singh (2022), Master Data Management includes a broad range of processes and technologies aimed at establishing a dependable 'single source of truth' for master data supporting operational and analytical activities. Likewise, Alfiandi and Ruldeviyani (2024) report that practical Master Data Management implementations significantly improve organisational transparency, efficiency, and decision-making.

The widespread adoption of Master Data Management is mainly driven by the increasing complexity and volume of enterprise data today. Sun et al. (2025) highlight that sectors such as railways face significant challenges in managing vast and diverse data sets, requiring advanced Master Data Management strategies that incorporate artificial intelligence and blockchain for improved scalability and security. Huang (2022) also affirms that integrating Master Data Management frameworks into university information systems facilitates unified data governance and enhances administrative effectiveness. Despite these advances, a noticeable gap remains between academic research and real-world implementation, particularly among small and medium-sized enterprises (SMEs). Factors such as limited financial resources, insufficient in-house technical expertise, and uncertainty around regulatory compliance often hinder the adoption of AI-driven Master Data Management solutions (Guerreiro et al., 2024; Krause & Becker, 2021). This review therefore aims to comprehensively examine current Master Data Management technologies, explore their applications across various industry domains, and identify ongoing challenges and research gaps. The scope covers 43 selected studies published between 2021 and 2025 that specifically address technological advancements, industrial applications, and governance frameworks. Conceptual papers without practical implementation or unrelated to core Master Data Management technologies were excluded from the review.

The study is guided by three key research questions.

(i) What are the key Master Data Management technologies currently implemented in practice?

(ii) How do these technologies perform across diverse industry domains?

(iii) What are the persistent challenges, limitations, and emerging opportunities that future research and development efforts should address?

By synthesising a wide range of studies, including those emphasising graph-based semantic methods (Nikolsky et al., 2023; Ramzy et al., 2022), blockchain-enabled access controls (Wang et al., 2022), and machine learning integrations (Chandrasekaran et al., 2025; Pansara et al., 2025), this review provides a comprehensive overview of the Master Data Management landscape. Considerations of maturity models (Alfiandi & Ruldeviyani, 2024; Schmuck, 2024), governance frameworks (Guerreiro et al., 2024), and organisational enablers further enrich our understanding of the socio-technical elements essential for effective Master Data Management implementation. This comprehensive review follows the structure proposed by Snyder (2019) for structured literature reviews in information systems research, emphasising transparency in the selection process, thematic organisation of findings, and alignment with research questions and objectives. The review begins with a synthesis of relevant literature to establish the current technological and industrial landscape of Master Data Management (Section 2). It is then followed by a description of the review methodology, including criteria for inclusion and exclusion (Section 3). Section 4 presents the results and key findings, mapped across Master Data Management technologies, industry domains, and implementation challenges. Finally, Section 5 concludes the paper by summarising the contributions and proposing future research directions to address ongoing gaps. This thorough approach aims to assist practitioners and researchers in identifying effective Master Data Management strategies tailored to their operational settings, while acknowledging the dynamic nature of technology and practice in this rapidly evolving field.

2. THEORETICAL FOUNDATION

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2.1 Master Data Management and Master Data

Master Data Management is centred on the need to create a unified, accurate, and consistent set of core business data, such as customers, products, and suppliers, across an organisation's various systems and processes (Sharma, 2024). While master data functions as the backbone for linking business transactions to key business entities, its effective management is essential for data quality, operational efficiency, and informed decision-making (Dahlberg et al., 2011; Raaccgnier-Paacccastaing & Gabassi, 2013). Master Data Management theory emphasises the integration of data, processes, and information systems, supported by clear data ownership, governance structures, and ongoing data quality practices (Martins et al., 2022). The concept of a "single source of truth" is central, aiming to eliminate data silos and ensure all departments operate from the same reliable information (Kaur et al., 2021). Therefore, Master Data Management is not merely an IT challenge but a managerial one, requiring organisational alignment, clearly defined roles and responsibilities, and a data-driven culture (Schmuck, 2024).

The theoretical frameworks for Master Data Management also consider the lifecycle of master data, from creation and maintenance to governance and eventual retirement, highlighting the importance of strategic, tactical, and operational perspectives (DAMA, 2017). As organisations become increasingly data-driven, Master Data Management and data governance have evolved from basic compliance functions to strategic enablers of business agility and innovation (Kalluri, 2024; Schmuck, 2025). Ultimately, the foundation of Master Data Management resides in its ability to support data governance, drive business success, and provide a sustainable competitive advantage through reliable and well-managed master data (Kalluri, 2024; Schmuck, 2025).

2.2 Master Data Management Technologies

Master Data Management technologies address the need for organisations to develop a unified, accurate, and consistent view of essential business data (customer, product, and supplier information) across different systems and departments (Kaur et al., 2021; Rodrigues & Carvalho, 2022). Master Data Management frameworks are founded on principles of data standardisation, governance, and integration, ensuring that critical data assets are dependable and accessible for operational and analytical purposes (DAMA, 2017). Over the past twenty years, Master Data Management has evolved from basic data quality and compliance functions to include cloud-native architectures, AI-driven automation, and multi-domain approaches that tackle the increasing complexity and volume of enterprise data (Kalluri, 2024; Sekhara et al., 2025). These advancements support real-time synchronisation, enhanced data governance, and better decision-making, supporting digital transformation in industries such as manufacturing, healthcare, and supply chain management (Bonthu & Goel, 2025; Pansara, 2023; Tian et al., 2023). The implementation of cloud-based Master Data Management further enhances scalability, flexibility, and integration with emerging technologies, such as IoT and blockchain, while robust security and governance frameworks ensure compliance and data integrity (Bonthu & Goel, 2025; Sekhara et al., 2025). In manufacturing, for example, Master Data Management facilitates effective collaboration, data sharing, and operational excellence throughout the product lifecycle (Pansara, 2023; Tian et al., 2023). Across various sectors, the application of Master Data Management technologies leads to improved data quality, operational efficiency, regulatory compliance, and a competitive advantage, thereby establishing Master Data Management as a strategic asset in the data-driven enterprise landscape (Bonthu & Goel, 2025; Kalluri, 2024; Sekhara et al., 2025).

2.3 DAMA Data Management Body of Knowledge (DAMA-DMBOK)

The DAMA Data Management Body of Knowledge (DAMA-DMBOK) related to Master Data Management is based on the idea that data is a valuable strategic asset that requires organised governance, quality oversight, and alignment with organisational goals. It provides a detailed framework for data management, emphasising the importance of clear policies, defined roles, and standardised processes to

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maintain data consistency, reliability, and value throughout the organisation (Hendrawan et al., 2022; Ismail et al., 2024; Sigi, 2024). This framework also emphasises the importance of data governance, data quality, and data security as essential for successful Master Data Management implementation (Hendrawan et al., 2022; Ismail et al., 2024; Khalimi, 2025). Key components of DAMA-DMBOK relevant to Master Data Management include Data Governance, Data Architecture Management, Data Modeling and Design, Data Storage and Operations, Data Security Management, Data Integration and Interoperability, Document and Content Management, Reference and Master Data Management, Data Warehousing and Business Intelligence, Metadata Management, and Data Quality Management (Hendrawan et al., 2022; Ismail et al., 2024; Ruslan et al., 2023; Sigi, 2024). Collectively, these elements offer a structured method for managing master data, ensuring its accuracy, security, and alignment with business needs throughout its lifecycle (Hendrawan et al., 2022; Ismail et al., 2024; Sigi, 2024).

2.4 Pinpointing Gaps in the Existing Research

Managing master data effectively remains a challenge due to the scattered and varied data sources. Nikolsky et al. (2023) highlight ergonomic and usability issues in traditional asset Master Data Management systems, resulting from the complex relationships among enterprise assets. Their research focuses on the importance of enhancing data modelling and user interface design to achieve more effective data analysis results. Olimpiev et al. (2023) reveal inherent challenges in implementing blockchain technology for semantic Master Data Management, emphasising issues related to data quality, security, interoperability, and storage efficiency. This highlights the complexities of integrating new technologies into existing Master Data Management frameworks. Further complicating the landscape, Lohmer et al. (2021) highlight that centralised platforms, often used for managing master data in supply chains, face risks such as reliance on intermediaries and limited data sovereignty, prompting the exploration of decentralised solutions like blockchain. Additionally, Krause and Becker (2021) show that in emerging areas such as the Internet of Things (IoT), system-level Master Data Management applications are prevalent but encounter scalability and integration issues due to the vastness and variability of device-generated data. Despite these challenges, a cross-sectoral comparative understanding of Master Data Management technologies remains limited. This gap hinders organisations' ability to adopt solutions that are most suited to their specific needs.

2.5 Synthesis and Link to Research Questions

The theoretical foundations discussed in this section collectively feature the multidimensional nature of Master Data Management, covering both technological and organisational aspects. The literature highlights that successful Master Data Management requires more than just data infrastructure; it needs strategic governance, domain-specific adaptation, and lifecycle-wide coordination, as outlined by the DAMA-DMBOK framework. While existing research offers valuable insights into Master Data Management concepts, technologies, and implementation contexts, significant gaps in knowledge remain, especially in understanding how these technologies perform across various industry sectors and how they address domain-specific challenges. These insights directly inform the study’s research questions: identifying key Master Data Management technologies, assessing their application across industries, and exploring limitations and opportunities for future development. Establishing this theoretical grounding ensures that the subsequent review and synthesis are not only descriptive but also analytically anchored in existing knowledge frameworks.

3. METHODOLOGY

This study employs a structured literature review methodology, as outlined by Snyder (2019), suitable for emerging fields with ongoing conceptual and practical development. Unlike traditional reviews, it systematically identifies, categorises, and analyses studies through transparent procedures. This approach is essential for exploring Master Data Management technologies across industries and their challenges.

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Following Snyder's typology, it is a "theory-building and refining" review, aiming to consolidate knowledge and identify research gaps. This rigorous method enhances credibility and contributes both academically and practically to Master Data Management frameworks.

3.1 Article Identification and Search Strategy

The article selection process began by defining clear search strategies aligned with the study's objectives. A structured Boolean search was conducted using the Scopus database to ensure comprehensive coverage of relevant literature. The search was restricted to peer-reviewed journal articles and conference proceedings published between 2021 and 2025, to ensure relevance to contemporary technological trends and implementation contexts. Additional searches were also conducted through IEEE Xplore, ACM Digital Library, and Google Scholar to capture supplementary studies. The following Boolean query string was used to retrieve documents related to Master Data Management technologies, their applications, and challenges across various industry domains:

Boolean Search String:

("master data management" AND (technology OR framework OR architecture OR platform) AND (implementation OR adoption OR application OR challenges))

The initial search yielded 101 documents, which were then subjected to screening based on title and abstract relevance (Table 1).

Table 1. Article search summary

Database / Source	Search String	Years	Results Retrieved
Scopus	("master data management" AND (technology OR framework OR architecture OR platform) AND (implementation OR adoption OR application OR challenges))	2021–2025	41
IEEE			18
ACM Digital Library			23
Google Scholar	Supplementary search		19
Total			101

3.2 Screening, Eligibility, and Article Selection Criteria

After the initial identification, a multi-stage screening process was implemented to ensure quality and relevance to the research questions (refer to Table 2).

Table 2. Criteria for article selection

Inclusion Criteria:	(i)	Articles published between 2021 and 2025.
	(ii)	Peer-reviewed journals or indexed conference proceedings.
	(iii)	Explicit discussion on Master Data Management technologies, implementation, frameworks, or industry applications.
	(iv)	Focused on technical, managerial, or organisational aspects of Master Data Management.
	(v)	Written in English.
Exclusion Criteria:	(i)	Studies that focus solely on data warehouses or enterprise systems without linking them to Master Data Management are not comprehensive.
	(ii)	Editorials, book reviews, and opinion papers.
	(iii)	Papers lacking access to full text (unless the abstract contained critical information).
	(iv)	Redundant or duplicated publications.

3.3 Literature Scoring Framework

To ensure a structured and transparent literature selection process, each of the 101 retrieved articles was evaluated based on predefined relevance criteria aligned with the study's research questions. A scoring framework was developed to guide the inclusion of articles into the final synthesis, with a focus on three core dimensions:

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(i) Identification of Master Data Management Technologies

Articles were assessed based on how clearly, they identified specific aspects of Master Data Management technologies, frameworks, or approaches. Scores ranged from 0 to 3, reflecting the level of detail and specificity in the discussion.

(ii) Definition of Application Domain

Each article was evaluated on whether it explicitly identified the industry or application area (such as healthcare, manufacturing, or education) where Master Data Management was applied. Up to 2 points could be awarded for this criterion.

(iii) Discussion on Challenges and Barriers

Articles that addressed common challenges, limitations, or implementation barriers related to Master Data Management, such as data integration, governance, or scalability, were awarded up to 2 points.

The maximum attainable score was 7 points, and articles that scored at least 4 points were believed sufficiently relevant and included in the final review. This systematic scoring approach allowed for the prioritisation of studies that most effectively addressed the core research questions, namely the identification of key Master Data Management technologies, their performance across various domains, and the persistent challenges surrounding their implementation. The final set of 43 articles selected is summarised in Appendix, which displays individual article scores across the three dimensions. This scoring mechanism enhanced the rigour of the literature review, ensuring that only high-relevance sources were synthesised for in-depth thematic analysis. Fig. 1 shows that out of the 101 initially retrieved articles, 43 articles were included in the final review based on relevance scoring and detailed content analysis.

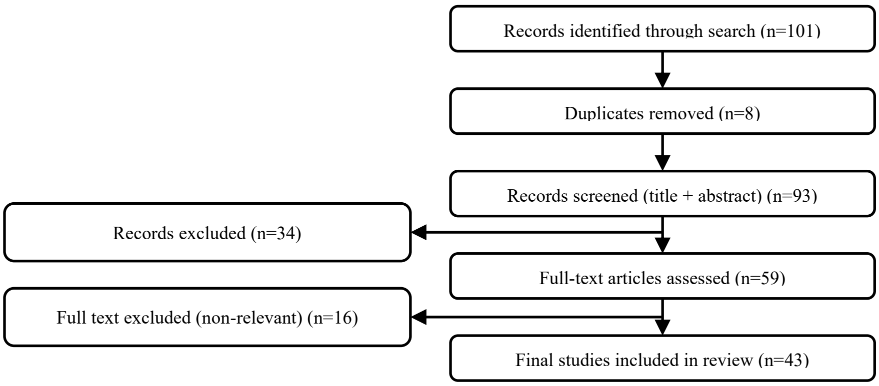

Fig. 1. Article selection process flow diagram

3.4 Analysing and Synthesising Selected Articles

The final set of 43 selected articles was critically reviewed and synthesised using thematic and descriptive analysis approaches. Each article was read thoroughly, and relevant information was extracted to answer the study's three research questions (Section 1.3). Thematic patterns were identified by grouping similar findings related to Master Data Management Technologies, frameworks, application contexts, and implementation challenges. The analysis was also mapped against the DAMA-DMBOK framework to ensure conceptual consistency with established data management principles. Key variables extracted from each article included (i) Type of Master Data Management technology or solution, (ii) Industry/application domain, (iii) Benefits and performance outcomes, (iv) Identified barriers and challenges, (v) Alignment with Master Data Management components in DAMA-DMBOK. The synthesis results are presented thematically in Section 4, highlighting qualitative insights, particularly for comparing Master Data

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Management practices across domains such as healthcare, education, supply chain, and the government sector.

4. RESULTS AND DISCUSSION

This section presents the findings of the structured literature review guided by the research questions (Section 1.3). The review synthesises evidence from 43 selected articles, grouped according to emerging technological themes and their application across industry domains. Each subsection addresses a specific research question through summarised tables and comparative discussion. A final thematic synthesis is conducted by mapping the reviewed technologies against the core Master Data Management components outlined in the DAMA (2017) framework, forming the basis for a proposed Master Data Management conceptual model.

4.1 What are the key Master Data Management technologies currently implemented in practice?

Master Data Management technologies help organisations manage and maintain accurate, consistent, and dependable data. Several technologies and frameworks are available, each offering unique advantages and challenges. Table 3 provides an overview of the primary Master Data Management technologies currently in use and is discussed in the next section. These include graph-based and semantic approaches, which aid in modernising asset management and enhancing data relationship analysis. Understanding these technologies and their applications can help organisations select the best solutions for their needs and address common data management issues.

Table 3. Master data management technologies currently implemented in practice

Technologies	Approaches	Benefits	Challenges	Author (Year)
Graph-based and semantic technologies	Annotated Meta graph: Modernises asset Master Data Management, multilayer relationships.	Improved usability, enhanced user interaction, and reduced errors.	Addresses ergonomic challenges in analysing data relationships.	Nikolsky et al. (2023)
	Knowledge-Graph-Based Master Data Management: common understanding, evolutionary master data model, stakeholder involvement	Enhanced master data integration, coherent supply chain analysis.	Supports semantic interoperability.	Ramzy et al. (2022)
	Knowledge Graph Integration with Retrieval-Augmented Generation (RAG): A Comparative Study of Graph-Based, Vector-Based, and Hybrid Methods.	Graph-based improved answer correctness by over 20%.	Harnesses structural richness for better context retrieval.	Tjokro and Sanjaya (2024)
	Semantic Data Management: Ontology-based access, semantic modelling, tailored to big data.	Prevents data swamps and ensures scalable data access.	Challenge: integrating heterogeneous data sources.	Hoseini et al. (2024)
Blockchain-Enabled Master Data Management Solutions	Ethereum-based permissioned: Supply chain Master Data Management, permissioned vs permissionless networks.	Better scalability, lower costs, and reduced. Centralisation risks.	Eliminates single points of failure, improves data sovereignty.	Lohmer et al. (2021)
	Blockchain ciphertext-policy attribute-based encryption (CP-ABE): Hybrid encryption, fine-grained access control.	Addresses privacy and security in data sharing.	Stores only essential information on the blockchain, relieving node storage.	Wang et al. (2022)

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Technologies	Approaches	Benefits	Challenges	Author (Year)
	Ethereum and InterPlanetary File System technologies: Semantic Master Data Management, modified algorithm.	Improves accuracy, consistency, and completeness.	Introduces storage inefficiencies due to blockchain overhead.	Olimpiev et al. (2023)
Artificial Intelligence and Machine Learning Integration	AI-assisted automation method: Large-scale data maintenance automation	Increases competitiveness, improves reliability.	Addresses manual approach limitations.	Riesener et al. (2022)
	Machine learning-powered Master Data Management: ML in Master Data Management for sustainable development	Improves data-driven decision-making.	Advancing resilient, equitable practices.	Pansara et al. (2025)
	Advanced ML for privacy, scalability, and compliance in life sciences.	Overcomes privacy issues, enhances compliance.	Addresses scalability constraints.	Vallepu (2024)
	Data governance and decision tree algorithms are utilised in the tenant management model.	Decreased data redundancy, improved efficiency.	Optimises resource allocation and decision-making.	Liu et al. (2025)
	Predicting diabetes prevalence using a stacked ML model (Informatica).	The accuracy of 81.16% surpasses individual classifiers.	Demonstrates AI/ML impact on Master Data Management	Chandrasekaran et al. (2025)
Frameworks and Models for Master Data Management Maturity and Governance	MD3M Maturity Model: assessed maturity in the Directorate General of Religious Courts	Identified gaps, recommended improvements.	Progress from baseline maturity level.	Alfiandi and Ruldeviyani (2024)
	Maturity Model: Six maturity levels, eight design areas, 23 factors	Emphasises organisational dimensions and efficiency.	Supports maturity evaluation.	Schmuck (2024)
	Maturity evaluations in educational institutions	Higher maturity by implementing missing capabilities.	Highlights the importance of systematic implementation.	Kaur and Singh (2023)
	Data Quality Framework at the Government Organisation in Indonesia	The importance of data quality for organisational success and decision-making processes.	Low data quality leads to adverse effects, including customer dissatisfaction and high operational costs.	Nulhusna et al. (2022)
	Master Data Management Standard framework to enhance Master Data Management maturity	Addresses ineffective, non-transparent implementations.	Complements maturity models.	Guerreiro et al. (2024)
	Risk data management, BCBS 239 compliance	Demonstrates mature governance frameworks.	Specialised Master Data Management applications.	Martins et al. (2022)
	Critical Success Factor (CSF), identified and ranked CSFs using AHP	Practical insights for overcoming challenges.	Addresses human, technical, and organisational barriers.	Raharjo et al. (2023)

4.1.1 Graph-Based and Semantic Technologies

Graph-based and semantic technologies have gained prominence in Master Data Management due to their ability to represent complex relationships and support semantic interoperability. Nikolsky et al. (2023) proposed an annotated meta graph to modernise asset Master Data Management by addressing ergonomic challenges in analysing data relationships. This approach enhances usability by presenting the multilayer relationships between enterprise assets in a more comprehensible manner, facilitating improved user interaction and reducing errors. Additionally, Ramzy et al. (2022) developed a knowledge-graph-based Master Data Management methodology that establishes a common understanding of key business entities and enables an evolutionary development of the master data model through stakeholder involvement. Their

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approach enhances master data integration, enabling coherent analysis of supply chain performance across stakeholders. Tjokro and Sanjaya (2024) further explored the integration of knowledge graphs with Retrieval-Augmented Generation (RAG) to enhance data traceability in Master Data Management environments. Their comparative study of graph-based, vector-based, and hybrid methods revealed that graph-based approaches significantly improved answer correctness by over 20%, harnessing the structural richness of knowledge graphs for better context retrieval. On the semantic data management front, Hoseini et al. (2024) surveyed ontology-based data access, semantic modelling for metadata enrichment, and semantic data management techniques tailored to big data environments such as data lakes. They highlight the challenge of integrating heterogeneous data sources into expressive, interoperable datasets, emphasising the role of semantic models in preventing data swamps and ensuring scalable data access.

4.1.2 Blockchain-Enabled Master Data Management Solutions

Blockchain technology presents an innovative solution to the challenges of security, decentralisation, and data integrity in Master Data Management. Lohmer et al. (2021) demonstrated the use of Ethereum-based permissioned blockchain networks for supply chain Master Data Management, concluding that permissioned networks offer better scalability and lower costs than permissionless alternatives. This design science study confirmed blockchain's potential to eliminate reliance on centralised platforms, reducing risks such as single points of failure and limited data sovereignty. Wang et al. (2022) integrated blockchain with ciphertext-policy attribute-based encryption (CP-ABE) to achieve fine-grained access control in Master Data Management systems, addressing privacy and security concerns during data sharing. Their hybrid encryption method stores only essential information (such as hash indexes and access control policies) on the blockchain, relieving storage pressure on nodes while maintaining tamper-proof capabilities. Olimpiev et al. (2023) contributed a modified dynamic data transformation algorithm leveraging Ethereum and IPFS technologies for semantic Master Data Management. Their approach enhances data accuracy, consistency, and completeness, although it introduces some storage inefficiencies due to the blockchain's overhead. Together, these studies demonstrate the utility of blockchain in enhancing data security, traceability, and governance within Master Data Management frameworks.

4.1.3 Artificial Intelligence and Machine Learning Integration

Artificial Intelligence (AI) and Machine Learning (ML) techniques have become vital tools for automating and improving the accuracy of Master Data Management processes. Riesener et al. (2022) presented an AI-assisted automation method that enables fast and reliable large-scale data maintenance, addressing the growing complexity of master data, which often overwhelms manual approaches. Their methodology facilitates digital business processes, significantly increasing organisational competitiveness through improved data reliability.

Machine learning-powered Master Data Management has also been applied to enhance sustainability efforts and data quality management. Pansara et al. (2025) investigated how ML methodologies integrated into Master Data Management systems foster sustainable development by improving data-driven decision-making, thereby advancing resilient and equitable practices. Vallepu (2024) analysed life sciences Master Data Management challenges, recommending advanced ML techniques to overcome data privacy issues and scalability constraints while enhancing compliance with regulatory mandates. Furthermore, Liu et al. (2025) designed a tenant management model for power utility Master Data Management leveraging data governance and decision tree algorithms. Their implementation resulted in decreased data redundancy and improved management efficiency, showcasing the efficacy of ML algorithms in optimising resource allocation and decision-making. Chandrasekaran et al. (2025) applied stacked machine learning models integrated with Informatica Master Data Management tools to predict diabetes prevalence, achieving an accuracy of 81.16%, which surpassed that of individual classifiers. These demonstrations highlight the increasing influence of AI and ML in enhancing the adaptability, efficiency, and precision of Master Data Management processes.

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4.1.4 Frameworks and Models for Master Data Management Maturity and Governance

Structured frameworks and maturity models provide organisations with pathways to evaluate and enhance their Master Data Management capabilities. Alfiandi and Ruldeviyani (2024) assessed the maturity level of Master Data Management within the Directorate General of the Religious Courts in Indonesia using the MD3M model. They identified current performance gaps and recommended strategic improvements to progress from a baseline maturity level. (Schmuck, 2024) extended Master Data Management maturity modelling by creating a comprehensive artefact encompassing six maturity levels and eight design areas, with 23 assessment factors that emphasise organisational dimensions and efficiency measurement. Kaur and Singh (2023) performed maturity evaluations in educational institutions, finding that the organisations can achieve higher maturity by implementing missing capabilities, thus highlighting the importance of systematic implementation.

Data governance frameworks complement maturity models by embedding governance practices into Master Data Management activities. Guerreiro et al. (2024) proposed a standard data governance framework to enhance Master Data Management maturity, tackling prior ineffective and non-transparent implementations. Martins et al. (2022) introduced a six-phase action plan focused on risk data management and BCBS 239 regulatory compliance in banking, demonstrating how mature governance frameworks intersect with specialised Master Data Management applications. Organisational success in Master Data Management initiatives also depends on critical success factors (CSFs). Raharjo et al. (2023) identified and ranked these CSFs through expert validation and Analytic Hierarchy Process (AHP) methodologies, providing practical insights to overcome implementation challenges. Their results help enterprises strategically address human, technical, and organisational barriers, ensuring better project outcomes. Collectively, these frameworks and governance approaches establish foundational strategies and practices for organisations to navigate complex Master Data Management landscapes effectively, supporting sustainable data management growth across sectors.

4.2 How do these technologies perform across diverse industry domains?

Master Data Management technologies are transforming key industries. They highlight the practical applications and benefits of Master Data Management in various sectors, including healthcare, life sciences, manufacturing, supply chain management, and energy. Through recent studies and real-world examples, these technologies improve data accuracy, efficiency, and compliance. The summary of the synthesis of Master Data Management technology is shown in Table 4. The following section will discuss and assess the unique challenges and solutions for each industry, demonstrating how Master Data Management supports informed decision-making and fosters sustainable business growth in a rapidly evolving data environment.

Table 4. Summary of synthesis of master data management technology across diverse industry domains

Domains	Technology	Benefits	Challenges	Author (Year)
Healthcare and Life Sciences	AI, semantic technologies, BMS-LM ontology, machine learning	Streamline workflows, ensure data accuracy and compliance, enhance interoperability, and improve data quality through reuse, annotation, and sharing. This also supports enhanced decision-making, automates and optimises processes, and facilitates scalability and standardisation.	Data-intensive workflows, data heterogeneity, regulatory compliance, data privacy, and managing massive datasets.	Kulkov (2021), Raboudi et al. (2022), Vallepu (2024)
Manufacturing and Supply Chain	Blockchain-based Master Data Management, Material Master Data	Data transparency, operational efficiency, secure data sharing, tamper-proof records,	Intermediary risks, stakeholder/infrastructure challenges, supply chain optimisation.	Lohmer et al. (2021), Merwe et al. (2024), Ramzy et al. (2022),

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Domains	Technology	Benefits	Challenges	Author (Year)
	Management, KnowGraph-Master Data Management	inventory turnover, order fulfilment accuracy, shorter lead times, semantic mappings, and robust data ingestion.		Andersen et al. (2022)
Energy and Utilities	Enterprise-level Master Data Management, master data tenant management model, decision tree algorithms	Increased database operation efficiency, >80% data reading/access efficiency, reduced data redundancy, optimised resource allocation, faster decision-making, and supports digital transformation.	Data consistency, operational efficiency, and resource allocation.	Hu et al. (2024), Liu et al. (2025)
IoT and Urban Infrastructure	Master Data Management in IoT, system-level Master Data Management, and semantic cloud technologies	20% improvement in data accuracy, 30% reduction in integration time, 15% decrease in costs, 40% increase in scalability, and an adaptive/secure/robust data framework.	Challenges include the complexity of connected devices, sustainable urban growth, and public infrastructure management.	Pansara et al. (2024), Krause and Becker (2021), Yang et al. (2021)
Transportation (Railways)	AI and blockchain-integrated Master Data Management framework	Classifies complex business data, supports dynamic updates, and enhances safety and operational efficiency.	Growing volume and complexity of data.	Sun et al. (2025)
Cultural Heritage	Microsoft SQL Server MDS web platform	Ensures data quality, versioning, auditing, and reliable long-term management.	Management of complex cultural assets.	Spettu et al. (2024)
Manufacturing (CRM)	Web-based Master Data Management systems	Enhances user satisfaction and operational efficiency.	Customer relationship management.	Patel et al. (2024)
Enterprise Systems	Knowledge graph-enhanced Master Data Management	Improves data traceability and request handling.	Complex data environments.	Tjokro and Sanjaya (2024)

Master Data Management has seen transformative applications in healthcare and the life sciences, particularly through the leveraging of artificial intelligence (AI) and semantic technologies. Kulkov (2021) demonstrates how AI has significantly impacted key business processes in pharmaceutical companies, including research and development, Master Data Management, and reporting. AI-supported Master Data Management enables pharmaceutical firms, especially small and medium enterprises, to streamline data-intensive workflows and ensure data accuracy and compliance. Furthermore, Raboudi et al. (2022) developed the BioMedical Study - Lifecycle Management (BMS-LM) ontology, which serves as a semantic framework to enhance the interoperability and reuse of biomedical data across heterogeneous knowledge systems. This ontology-based Master Data Management approach facilitates better data annotation and sharing, addressing the inherent heterogeneity in biomedical metadata. In the life sciences sphere, challenges such as managing massive and diverse datasets, ensuring regulatory compliance, and maintaining data privacy persist. Vallepu (2024) highlights that integrating machine learning techniques into life sciences Master Data Management systems can effectively address these issues by enhancing data quality management and decision-making capabilities. The application of AI to automate and optimise master data processes in clinical research further enhances scalability and standardisation in managing complex datasets.

The manufacturing and supply chain sectors have embraced Master Data Management technologies to improve data transparency and operational efficiency. Lohmer et al. (2021) investigate blockchain-based Master Data Management systems for securing data sharing across supply chain partners, thereby reducing risks linked to intermediary dependencies and ensuring tamper-proof record-keeping. This use of permissioned blockchain networks provides scalability and lower operational costs compared to

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permissionless options. Merwe et al. (2024) studied Material Master Mata Management (MMDM) at FLSmidth, showing that effective MMDM enhances inventory turnover, improves accuracy in order fulfilment, and shortens lead times. Their research highlights the importance of strategic collaborations with external service providers to address stakeholder and infrastructure challenges, which often hinder the success of Master Data Management. Additionally, Ramzy et al. (2022) introduced a knowledge graph approach (KnowGraph-Master Data Management) for integrated supply chain performance analysis. This method supports a consistent master data model that considers diverse stakeholder viewpoints, enabling sophisticated semantic mappings and robust data ingestion, which are vital for supply chain optimisation.

Enterprise-wide Master Data Management implementations in the energy and utilities domain improve data consistency and operational efficiency. Hu et al. (2024) verified that deploying an enterprise-level Master Data Management system significantly increased database operation efficiency in electric power enterprises, with performance metrics surpassing 80% efficiency in data reading and access, exceeding traditional methods. Additionally, Liu et al. (2025) presented a master data tenant management model for the State Grid Corporation of China, which combines data governance frameworks with decision tree algorithms. This model effectively reduces data redundancy while optimising resource allocation and decision-making speed, supporting the digital transformation of power enterprises.

Master Data Management plays a pivotal role in IoT ecosystems and urban infrastructure. Pansara et al. (2024) quantitatively demonstrated that implementing Master Data Management in IoT ecosystems results in a 20% improvement in data accuracy, a 30% reduction in data integration time, a 15% decrease in operational costs, and a 40% increase in ecosystem scalability. These benefits reinforce the role of Master Data Management in enhancing the efficiency and adaptability of innovative city data management. (Krause & Becker, 2021) analysed Master Data Management applications specific to IoT and highlighted the dominance of system-level Master Data Management designs, underscoring their importance for managing the complexity of connected devices. Yang et al. (2021) proposed a Master Data Management approach that leverages IoT and semantic cloud technologies to address the challenges of sustainable urban growth. Their solution provides an adaptive, secure, and robust data framework essential for smart city programs aiming to improve the quality of life through better public infrastructure management. The transportation sector, particularly railways, benefits from integrating AI and blockchain within Master Data Management systems to handle the growing volume and complexity of data. Sun et al. (2025) introduced an intelligent Master Data Management framework that combines these technologies to effectively classify complex business data and support dynamic updates, thereby enhancing the safety and operational efficiency of railway systems.

Beyond traditional industrial domains, Master Data Management approaches have been applied to cultural heritage management. Spettu et al. (2024) utilised Microsoft SQL Server Master Data Services to develop a web platform for managing extended cultural heritage databases such as the Sacri Monti in Italy. This Master Data Management-driven platform ensures data quality, versioning, and auditing, which are essential for maintaining the reliable and long-term management of complex cultural assets. Additional applications include customer relationship management in manufacturing through web-based Master Data Management systems, which enhance user satisfaction and operational efficiency (Patel et al., 2024). The deployment of knowledge graph-enhanced Master Data Management also improves data traceability and request handling within enterprise systems (Tjokro & Sanjaya, 2024). These varied applications underscore the versatility of Master Data Management across diverse sectors and complex data environments.

4.3 What are the persistent challenges, limitations, and emerging opportunities that future research and development efforts should address?

This section examines the primary challenges, limitations, and prospects of Master Data Management across various industries. It considers common barriers organisations face with Master Data Management systems, such as difficulties in achieving collaboration and resolving technical issues. A summary of the

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key barriers, challenges, and findings related to Master Data Management is presented in Table 5. The discussion also addresses issues related to maintaining data accuracy and consistency, as well as complying with strict rules and standards. By understanding these obstacles and emerging opportunities, businesses and researchers can develop more effective ways to manage and utilise their critical data.

Table 5. Summary of master data management key barriers, challenges and findings

Key Barriers	Challenges	Findings	Author (Year)
Organisational	Aligning stakeholders, securing infrastructure.	Convincing stakeholders and establishing adequate infrastructure were significant barriers.	Merwe et al. (2024)
Technical	Diverse data sources, integration complexity.	Scattered, poorly integrated data complicates synchronisation, consolidation, and cleaning.	Singh and Singh (2022)
	Data integration and ETL process difficulties.	Inconsistent data formats and standards hinder the seamless flow of data.	Sreemathy et al. (2021)
	Legacy IT system limitations.	Early IT lacked planning for data standards and exchange protocols, causing inconsistencies.	Hu et al. (2024)
Data Quality	Duplicate detection, noisy datasets.	Graph-partitioning method for entity resolution in retail receipt product names.	Ilagan and Ilagan (2024)
	Duplicate record removal.	Record linkage tools to create a reliable master dataset for lecturer records.	Amin et al. (2023)
	Automating quality verification	Rule-based, dictionary-based, and ML methods can validate product data, but they require careful design and some manual effort.	Niemir and Mrugalska (2023)
	Lack of comprehensive quality management frameworks.	Failing to consider key factors can erode trust and lead to flawed business decisions.	Ibrahim et al. (2024)
Regulatory/Compliance	Aligning with regulatory requirements (e.g., BCBS 239).	Six-phase action plan for banks; technical and functional complexities in compliance.	Martins et al. (2022)
	Data privacy and security mandates.	Life sciences Master Data Management faces challenges due to the diverse nature of clinical data and stringent privacy regulations.	Vallepu (2024)
	Technological Challenges in Privacy and Security Solutions.	Blockchain-based Master Data Management with cryptographic access controls introduces significant complexities in storage and integration.	Wang et al. (2022)

Implementing Master Data Management systems in organisations often faces significant organisational and technical challenges that can hinder success. A major obstacle is aligning stakeholders and securing the required infrastructure. Merwe et al. (2024) highlighted in their study of material master data management at FLSmidth that convincing stakeholders and establishing adequate infrastructure were significant barriers during implementation. Without a shared commitment from stakeholders, Master Data Management initiatives risk becoming disjointed and less effective.

Furthermore, the challenge of managing diverse data sources and data integration adds significant technical complexity. Singh and Singh (2022) noted that many organisations deal with scattered and poorly integrated data across various systems and formats, which complicates synchronisation, consolidation, and data cleaning. This problem is particularly acute in organisations with operational silos, resulting in inefficiencies and inconsistencies in master data management. Supporting this, Sreemathy et al. (2021) emphasised that data integration, especially in Extract, Transform, Load (ETL) processes, is crucial for business intelligence but is often encountered with difficulties due to inconsistent data formats and standards. The lack of standardised integration frameworks further complicates ensuring seamless data flow between sources. Other technical barriers include the inherent limitations of legacy IT systems that were not initially designed for unified master data governance. Hu et al. (2024) studied the informatisation of the

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power enterprise and observed that early IT development frequently lacked thorough planning for data standards and exchange protocols across different systems. These gaps lead to data inconsistencies, integrity problems, and limited auditability, all of which are vital for the success of Master Data Management systems.

Ensuring data quality and consistency is a persistent challenge in implementing Master Data Management. A key issue is detecting and resolving duplicate records in large, noisy datasets. Ilagan and Ilagan (2024) addressed this issue in retail, where digitised receipt product names contain errors such as substitutions, insertions, and deletions, complicating data linking. They proposed a graph-partitioning method for entity resolution that enhances clustering and mitigates the impact of noise. Similarly, Amin et al. (2023) addressed the removal of duplicate lecturer records from multiple sources using record linkage tools to create a reliable master dataset. Niemir and Mrugalska (2023) studied data science issues in automating verification for extensive product catalogues. Their findings showed that rule-based, dictionary-based, and machine learning methods can validate and detect errors in product data but require careful design for diverse and large datasets. They highlighted that manual effort is still needed in some cases to ensure accuracy. Additionally, Ibrahim et al. (2024) found that many current master data quality management frameworks lack comprehensive practices for maintaining quality across various dimensions and domains. Their research confirmed a series of key factors essential for effective master data quality management; ignoring these can result in decreased trust in the data and flawed business decisions.

Regulatory and compliance challenges pose another significant obstacle to the implementation of Master Data Management, particularly in highly regulated sectors such as banking and finance. Martins et al. (2022) developed a novel six-phase action plan to help banks align their Master Data Management and data governance activities with BCBS 239 regulatory requirements for risk data aggregation and reporting. They highlighted the technical and functional complexities involved in establishing compliant master data processes that ensure data quality, traceability, and security across domains. Failure to meet these standards not only risks regulatory penalties but also diminishes the effectiveness of risk management. Moreover, compliance concerns intersect with data privacy requirements, which are increasingly stringent worldwide. Vallepu (2024) noted that life sciences Master Data Management faces significant challenges due to the massive and diverse nature of clinical data, which is further complicated by regulatory mandates that enforce data privacy and security. These factors restrict standardisation and sharing practices essential for efficient Master Data Management but are indispensable for adherence to legal frameworks. Lastly, Wang et al. (2022) examined blockchain-based Master Data Management methods addressing privacy and security issues through fine-grained access controls implemented via cryptographic algorithms. While effective in enhancing regulatory compliance, such solutions also bring technological challenges, including high storage demands and integration complexities.

4.4 Comparative Summary and Contextual Trade-offs of Master Data Management Technologies

To enhance the interpretive insights of the findings, this section presents a cross-comparative summary of the Master Data Management technologies reviewed. Table 6 below synthesises the key advantages, limitations, and contextual suitability of each technology group based on the analysis in Sections 4.1–4.3. This approach provides a clearer understanding of the trade-offs and assists stakeholders in evaluating Master Data Management options according to their organisational and industry-specific requirements.

Table 6. Comparison and contextual trade-offs of master data management technologies

Master Data Management Technology	Key Advantages	Limitations	Contextual Suitability	DAMA-DMBOK Component(s)
Graph-Based and Semantic Technologies	Excellent at modelling complex relationships.	Requires high design effort (ontology);	Healthcare, IoT, and supply chains with diverse entities.	Data Modelling, Metadata, Data Integration

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Master Data Management Technology	Key Advantages	Limitations	Contextual Suitability	DAMA-DMBOK Component(s)
	Supports semantic interoperability.	Limited scalability for large-scale real-time data.		
Blockchain-Enabled Master Data Management	High data integrity, decentralisation, secure sharing.	High storage and energy costs. Integration complexity.	Supply chain, finance, and regulated environments.	Data Security, Data Governance
AI and ML Integration	Automation, error detection, and scalable data cleaning.	Requires large, labelled datasets. Black-box nature can reduce explainability.	Healthcare, Utilities, Manufacturing.	Data Quality, Data Integration, Data Governance
Maturity and Governance Frameworks	Assists in Master Data Management planning, assessment and control.	May be rigid or generic if not tailored to specific organisations.	Public sector, banking, and education.	Data Governance, Data Quality, Reference and Master Data
Domain-specific Implementations (e.g. IoT, Life Sciences)	Context-sensitive design improves relevance and value.	High dependency on domain knowledge and existing infrastructure.	Smart cities, pharmaceutical R&D, and power grid.	All applicable components based on the implementation focus

This comparative analysis shows that no single Master Data Management technology outperforms others in all situations. Graph-based approaches allow for semantic precision and flexibility, especially in environments with high data diversity, such as healthcare and IoT. However, they often involve complex schema design and expert maintenance. Blockchain offers strong security and traceability, particularly in regulated industries, but it also brings performance and interoperability challenges. The integration of AI and ML significantly improves automation and scalability in Master Data Management processes. However, these methods require substantial data resources and careful oversight to ensure fairness and transparency. Governance frameworks and maturity models offer structured guidance, particularly for public or compliance-focused sectors, but they can become overly general without suitable contextual adaptation. These trade-offs highlight the importance of aligning technology choices with sector-specific needs, organisational maturity, and strategic data objectives. The DAMA-DMBOK framework serves as a unifying reference to ensure that, regardless of the technology chosen, crucial aspects such as Data Quality, Metadata, and Data Governance are consistently addressed. The thematic analysis in Appendix A summarised the final findings from the literature.

4.5 Proposed Conceptual Framework

The conceptual framework developed from this review synthesises the layered interactions between core master data components, enabling technologies and frameworks, and the strategic outcomes sought by organisations implementing Master Data Management initiatives. This model provides a structured perspective for understanding how foundational data practices, when supported by emerging technologies, can generate significant organisational impacts across industries. At the foundational level, the framework incorporates key domains from the DAMA-DMBOK knowledge areas, such as data governance, data quality, metadata management, reference and master data, interoperability, and security and privacy management, which function as the core components of Master Data Management (DAMA, 2017). These elements form the essential building blocks for any successful Master Data Management strategy, ensuring consistency, control, and integrity throughout the data lifecycle. The middle layer presents enabling technologies and frameworks that have appeared in the literature as essential drivers in contemporary Master Data Management practices. This includes:

(i) Artificial Intelligence and Machine Learning support automation, predictive analytics, and anomaly detection (Riesener et al., 2022; Pansara et al., 2025; Vallepu, 2024; Liu et al., 2025; Chandrasekaran et al., 2025).

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(ii) Blockchain enables data integrity, decentralised control, and secure access mechanisms (Lohmer et al., 2021; Wang et al., 2022; Olimpiev et al., 2023).

(iii) Semantic technologies and Knowledge Graphs improve interoperability, traceability, and semantic integration across systems (Nikolsky et al., 2023; Ramzy et al., 2022; Tjokro & Sanjaya, 2024; Hoseini et al., 2024).

(iv) Maturity and governance frameworks enable organisations to assess their capabilities, identify gaps, and guide structured improvement (Alfiandi & Ruldeviyani, 2024; Schmuck, 2024; Kaur & Singh, 2023; Guerreiro et al., 2024; Martins et al., 2022; Raharjo et al., 2023).

Finally, the top layer of the framework defines the strategic outcomes organisations aim to achieve through effective Master Data Management implementation. These include regulatory compliance, operational efficiency, data-driven decision-making, sustainability and innovation, and cross-domain integration (Merwe et al., 2024; Singh & Singh, 2022; Sreemathy et al., 2021; Hu et al., 2024; Ilagan & Ilagan, 2024; Amin et al., 2023; Niemir & Mrugalska, 2023; Ibrahim et al., 2024; Martins et al., 2022; Vallepu, 2024; Wang et al., 2022). The vertical arrow indicates the directional flow from fundamental components towards strategic outcomes, highlighting the transformative potential of Master Data Management when supported by strong practices and emerging technologies. The horizontal arrow represents the application of Master Data Management technologies and practices across industries, illustrating how sectoral contexts influence these technologies and their strategic outcomes. This framework can assist both practitioners and researchers in aligning Master Data Management initiatives with changing organisational demands and technological progress (refer to Fig. 2).

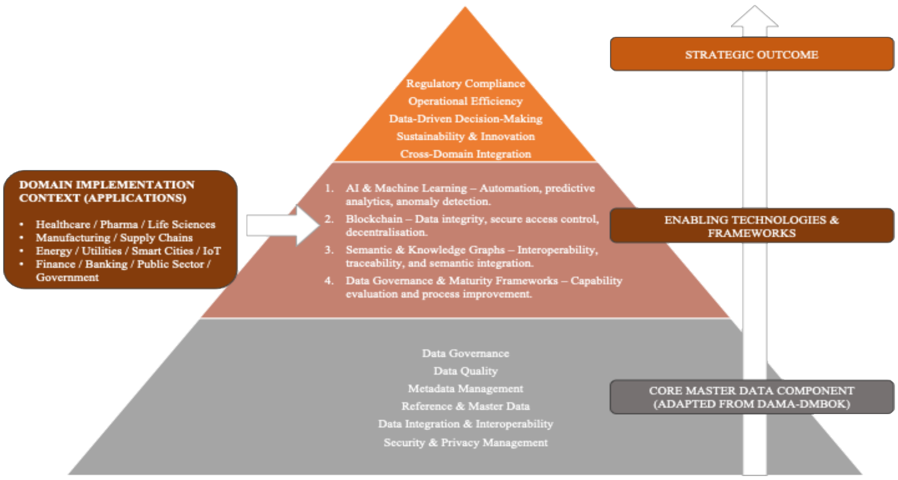

Fig. 2. Conceptual framework adopted and adapted from the reviewed literature

5. CONCLUSION

The review highlights the significant development of Master Data Management technologies, evolving from traditional methods to advanced solutions that include artificial intelligence, blockchain, and semantic

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knowledge graphs. In various sectors, including manufacturing, healthcare, energy, government, retail, and transportation, Master Data Management has played a crucial role in enhancing data quality, governance, and operational efficiency. Despite these advances, challenges persist in managing data integration complexity, achieving scalability, ensuring security, and complying with regulatory standards. Addressing these issues requires continued innovation in AI-driven automation, decentralised blockchain architectures, and semantic interoperability. Future research should focus on developing adaptable and scalable Master Data Management frameworks that incorporate cutting-edge AI and hybrid blockchain models, as well as establishing best practices for cross-industry collaboration and governance. These efforts will be vital in unlocking the full potential of Master Data Management to support data-driven decision-making and digital transformation globally.

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Farah Azleen carried out the study, wrote and revised the article. Dr. Suraya conceptualised the central study idea and provided the theoretical background. Farah Azleen designed the study, and Dr. Suraya supervised the article's progress. Dr. Suraya led the review and revisions and approved the article submission.

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APPENDIX

Table 7. Scoring table for study selection

ID	Title	Citation	Relevance to Master Data Management Technologies (0-3)	Clarity of Application Domain (0-2)	Discussion on Challenges and Barriers (0-2)	Final Score (out of 7)
A1	Improving the Ergonomics of the Master Data Management System Using Annotated Metagraph	Nikolsky et al. (2023)	3	2	2	7
A2	Improvement Master Data Management: Case Study Of The Directorate General Of The Religious Courts Of The Supreme Court Of The Republic Of Indonesia	Alfiandi and Ruldeviyani (2024)	3	2	2	7
A3	A Survey on Master Data Management Techniques for Business Perspective	Singh and Singh (2022)	1	1	2	4
A4	Real-Time Ml Enhanced Diabetic Prediction and Visualization with Informatica MDM Integration	Chandrasekaran et al. (2025)	3	2	2	7
A5	Blockchain-Based Master Data Management in Supply Chains: A Design Science Study	Lohmer et al. (2021)	3	2	2	7
A6	Preliminary Research to Propose a Master Data Management Framework Aimed at Triggering Data Governance Maturity	Guerreiro et al. (2024)	3	1	2	6
A7	Design and Development of University Information System Based on MDM-A Case Study of the Service Satisfaction Evaluation System	Huang (2022)	2	2	2	6
A8	Scenarios for the Use of Master Data Management in the Context of the Internet of Things (IoT)	Krause and Becker (2021)	2	2	2	6
A9	Modification of the Algorithm for Dynamic Data Transformation Based on Blockchain Technology for Data Management Systems	Olimpiev et al. (2023)	3	2	2	7
A10	Information Systems and Circular Manufacturing Strategies: The Role of Master Data	Andersen et al. (2022)	2	2	1	5
A11	A Model of Critical Success Factors for Master Data Management Development Projects using Analytic Hierarchy Process (AHP): An Insight from Indonesia	Raharjo et al. (2023)	3	1	2	6
A12	Application Research on the Master Data Tenant Management Model of State Grid Corporation Based on Data Governance and Decision Tree Algorithm Analysis	Liu et al. (2025)	3	2	2	7
A13	Enhancing Data Traceability: A Knowledge Graph Approach with Retrieval-Augmented Generation	Tjokro and Sanjaya (2024)	3	1	2	6
A14	Master data management method based on Blockchain and CP-ABE	Wang et al. (2022)	3	1	2	6
A15	Research on New Railway Master Data Management Technology Based on Artificial Intelligence and Blockchain	Sun et al. (2025)	2	2	2	6

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ID	Title	Citation	Relevance to Master Data Management Technologies (0-3)	Clarity of Application Domain (0-2)	Discussion on Challenges and Barriers (0-2)	Final Score (out of 7)
A16	Master Data Quality Management Framework: Content Validity	Ibrahim et al. (2024)	3	1	2	6
A17	Data management for customer relationship management: a web-based approach	Patel et al. (2024)	1	2	1	4
A18	Enhancing Sustainable Development Through Machine Learning-Driven Master Data Management	Pansara et al. (2025)	3	1	2	6
A19	Data Integration and ETL: A Theoretical Perspective	Sreemathy et al. (2021)	2	1	2	5
A20	Enhancing IoT Ecosystems through Effective Master Data Management	Pansara et al. (2024)	2	1	2	5
A21	A survey on semantic data management as intersection of ontology-based data access, semantic modeling and data lakes	Hoseini et al. (2024)	3	1	2	6
A22	Strategy to Improve Data Quality Management: A Case Study of Master Data at Government Organization in Indonesia	Nulhusna et al. (2022)	3	1	2	6
A23	Data Science Challenges of Automated Quality Verification Process in Product Data Catalogues	Niemir and Mrugalska (2023)	2	1	2	5
A24	Master Data Management Maturity Evaluation: A Case Study in Educational Institute	Kaur and Singh (2023)	3	2	2	7
A25	Strategies for Master Data Management: A Case Study of an International Hearing Healthcare Company	Haug et al. (2023)	1	2	2	5
A26	The need for local adaptation of smart infrastructure for sustainable economic management	Yang et al. (2021)	1	2	2	5
A27	Critical Data Consolidation in MDM to Develop the Unified Version of Truth	Kaur et al. (2021)	1	1	2	4
A28	The role of artificial intelligence in business transformation: A case of pharmaceutical companies	Kulkov (2021)	3	2	2	7
A29	Master Data Management As Part of Data Governance: A Maturity Model to Improve Efficiency and Trust in Master Data and Thus Business Performance	Schmuck (2024)	3	1	2	6
A30	A Data Quality Model for Master Data Repositories	Gualo et al. (2023)	3	1	2	6
A31	Risk compliance and master data management in banking – A novel BCBS 239 compliance action-plan proposal	Martins et al. (2022)	3	2	2	7
A32	Master Data Management using Record Linkage Toolkit for Integrating Lecturer Master Data	Amin et al. (2023)	2	2	2	6
A33	The BMS-LM ontology for biomedical data reporting throughout the lifecycle of a research study: From data model to ontology	Raboudi et al. (2022)	3	2	2	7
A34	Towards master data management for cultural heritage: The sacri monti web platform	Spettu et al. (2024)	3	2	2	7
A35	Effects of material master data management on supply chain performance at FLSmidth: the moderating role of PiLog external service provider	Merwe et al. (2024)	1	2	2	5
A36	Data Quality Optimization for Decision Making Using Ataccama Toolkit: A Sustainable Perspective	Jamal et al. (2023)	2	1	2	5

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ID	Title	Citation	Relevance to Master Data Management Technologies (0-3)	Clarity of Application Domain (0-2)	Discussion on Challenges and Barriers (0-2)	Final Score (out of 7)
A37	Synergistic Integration of Master Data Management and Expert System for Maximizing Knowledge Efficiency and Decision-Making Capabilities	Pansara et al. (2024)	2	1	2	5
A38	Application of Enterprise Master Data Management System in the Informatization of Electric Power Enterprises	Hu et al. (2024)	3	2	2	7
A39	KnowGraph-MDM: A Methodology for Knowledge-Graph-based Master Data Management	Ramzy et al. (2022)	3	2	2	7
A40	Master Data Management	Rodrigues and Carvalho (2022)	1	1	2	4
A41	Tackling Challenges in Life Sciences Master Data Management Through Effective Machine Learning Implementation	Vallepu (2024)	2	2	2	6
A42	Graph-partitioning entity resolution for resolving noisy product names in OCR scans of retail receipts	Ilagan and Ilagan (2024)	2	2	2	6
A43	Methodology for Automated Master Data Management using Artificial Intelligence	Riesener et al. (2022)	3	1	2	6

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Table 8. Thematic analysis from the reviewed literature

Master Data Management Technologies	Industry/Application Domains	Master Data Management Components (DAMA-DMBOK)											Challenges				Authors
		DA	DM & D	DS & O	DS	DII	D & CM	R & MD	DW & BI	Metadata	DQ	DG	Organisational	Technical	Quality	Regulatory Compliance	
Graph-based and semantic technologies	Information Systems, Supply Chain, Industry 4.0, Biomedical, Retail	X	X	X		X	X		X	X	X	X	X	X	X	X	Hoseini et al. (2024), Ramzy et al. (2022) Raboudi et al. (2022), Tjokro and Sanjaya (2024), Ilagan and Ilagan (2024)
Blockchain	Healthcare, Transportation, Supply Chain, Logistics	X		X	X	X	X	X		X	X	X	X	X	X	X	Banerjee (2025), Lohmer et al. (2021), Olimpiev et al. (2023), Sun et al. (2025), Wang et al. (2022)
Artificial Intelligence	Pharmaceutical, Transportation			X	X	X						X	X	X	X	X	Kulkov (2021), Riesener et al. (2022), Sun et al. (2025)
Machine Learning	Healthcare, Life Science, Product Data Catalogue, Utility (Power Management)		X	X	X			X		X	X		X	X	X	X	Chandrasekaran et al. (2025), Liu et al. (2025), Niemir and Mrugalska (2023), Pansara et al. (2025), Vallepu (2024)
Maturity Model Governance Framework	Educational Institute, Government		X		X	X					X	X	X	X	X	X	Schmuck (2024), Kaur and Singh (2023), Guerreiro et al. (2024), Nulhusna et al. (2022),
Risk Data Management	Banking		X		X	X					X	X	X	X	X	X	Martins et al. (2022)
Data Quality Management Framework	Cultural Heritage, Across Domain	X	X	X		X		X	X	X	X	X	X	X	X	X	Ibrahim et al. (2024), Jamal et al. (2023), Nulhusna et al. (2022), Spettu et al. (2024)
Cloud-based Asset Management and Big Data Analytics	IoT		X					X			X	X	X	X	X	X	Krause and Becker (2021), Pansara et al. (2024), Yang et al. (2021)

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Master Data Management Technologies	Industry/Application Domains	Master Data Management Components (DAMA-DMBOK)											Challenges				Authors
		DA	DM & D	DS & O	DS	DII	D & CM	R & MD	DW & BI	Metadata	DQ	DG	Organisational	Technical	Quality	Regulatory Compliance	
Master Data Management Framework (Database Merging and Record Linkage, Data Management, Techniques)	Healthcare, Education, SMEs, Material Management	X	X	X	X			X		X	X		X	X	X	X	Amin et al. (2023), Haug et al. (2023), Kaur et al. (2021), Singh and Singh (2022), Merwe et al. (2024)
Circular Manufacturing Strategy, Regulatory compliance, Critical Success Factors (CSF)	Manufacturing, Organisation		X			X		X		X	X	X	X	X	X	X	Andersen et al. (2022), Gualo et al. (2023), Singh and Singh (2022), Raharjo et al. (2023)
Enterprise Systems, ETL, Web-based Approach	Information Systems Development/Implementation	X	X	X		X		X	X	X	X		X	X	X	X	Hu et al. (2024), Huang (2022), Pansara et al. (2024), Patel et al. (2024), Sreemathy et al. (2021)

DA: Data Architecture; DM & D: Data Modelling & Design; DS & O: Data Storage & Operation; DS: Data Security; DII: Data Integration & Interoperability; D & CM: Document & Content Management; R & MD: Reference & Master Data; DW & BI: Data Warehousing & Business Intelligence; Metadata; DQ: Data Quality; DG: Data Governance.

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