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The Roles of Electronic Records Metadata (ERM) in Artificial Intelligence (AI) Growth

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ABSTRACT

The paper highlights the roles of Electronic Records Metadata (ERM) in supporting the development of Artificial Intelligence (AI) in organizations. The issues occurred where the AI does not embed the ERM as part of its requirement in developing and manging the system in organizations. These include issues of inability of ERM in supporting any system in organizations which generated from AI technology. Based in these issues, the relationship between ERM and AI require a proper investigation in terms of its relation and connection. This issue has remained unsolved because it is still being discussed by scholars until today. This is where the main objective of this paper is to explore the roles of ERM in AI growth. Applying the method of Systematic Review Technique, the process of identifying the roles of ERM in AI are conducted adequately. Through the information gathered, the findings shows that there are Six (6) roles of ERM are gathered. There are data discovery and access, provenance and trustworthiness, interoperability, ethical and responsibility, quality of training, and long-term sustainability. Part of the relationship highlighted is ensuring whether the data that being generated by AI can be trusted or not. By embedding the ERM as part of AI system requirements, the data that being generated by any related system can be accessed, recovered and traced effectively. Through this justification, it has shown that the roles of ERM in AI are not only for its growth, but it is also can serve as evidence on any legal obligation.

Keywords: Roles, Electronic Records, Electronic Records Metadata (ERM), Artificial Intelligence (AI), Growth

INTRODUCTION

In the digital age, artificial intelligence (AI) has become a disruptive force in several industries, including healthcare, finance, education, and governance. The value and organization of the data that AI systems handle, have a significant impact on their efficacy, dependability, and credibility. Metadata, or the descriptive and contextual information connected to electronic records, is an important but frequently disregarded part of this environment. Machine interpretation, discovery, organization, and ethical use of information are made possible by metadata. Metadata for electronic records is therefore essential to the development and sustainability of AI. The six main purposes of metadata in AI development are examined in this article which includes a data discovery and access, provenance and trustworthiness, interoperability, ethical and responsible AI, quality of AI Training, and long-term sustainability and reproducibility.

LITERATURE REVIEW

In this section, the details explanation on each element that related to the topic is discussed. This includes the explanation on the aspect of execution of electronic records metadata in AI environment. In fact, this could facilitate the entire understanding of the roles of electronic records metadata in AI growth scalability. Sequentially, the next section is divided into six subsections in order to achieve the maximum output of understanding regarding the relationship between ERM and AI. By having the details explanation on next subsections paragraph, it is believed that the roles of ERM in AI growth can adequately justified.

2.1 Facilitating Data Discovery and Access

In brief, the ERM plays a critical role in facilitating data discovery and access within AI development. These include providing structured and descriptive information that enhances searchability and contextual understanding of datasets. In fact, the metadata itself contain the elements such as keywords, provenance, and format descriptors which could enable AI systems to efficiently index and retrieve relevant data across heterogeneous sources (Park, 2009; Xu, Jin, & Zhou, 2020). Furthermore, standardized metadata schemas can improve interoperability, making datasets more accessible for machine learning applications (Brase, 2009; Lagoze & Van de Sompel, 2001). On top of that, the enrichment of metadata thus accelerates AI training by streamlining data preparation processes could reducing the manual data curation efforts (Greenberg, 2009; Larmande et al., 2011). Through this justification, this shows that the role of ERM in facilitating data discovery and access is firmly justified. Thus, this also concludes that the well-structured of metadata becomes essential infrastructure for scalable and intelligent of any data that relates to AI systems and applications.

2.2 Establishing Provenance and Trustworthiness

In terms of provenance and trustworthiness, ERM shows its importance through maintaining the validity of metadata in AI applications. As to ensure that importance highlighted, it is importance to understand the provenance of metadata. There are several scholars has stated the definition of Provenance metadata. The provenance includes maintaining and capturing the ERM in terms of its origin, creation date, processing history, and ownership of data. This is because this element can enable the AI developers and users to trace how datasets were generated and manipulated over time, which is vital for model validation and ethical accountability (Moreau & Growth, 2013; Zeng et al., 2020). Meanwhile, in terms of ERM transparency, it can foster trust by allowing reproducibility and auditing of AI outcomes, particularly in high stakes of domains like healthcare, finance, or criminal justice (Davidson & Freire, 2008; Gil et al., 2013). Additionally, according to Herschel et al. (2017), the trustworthy metadata enhances the credibility of AI models by mitigating risks of data tampering and facilitating compliance with data governance on any frameworks applied in organisations. Overall, the provenance of ERM provides rich metadata in place which serves as a foundational element in the development of responsible and transparent AI.

2.3 Enabling Data Interoperability

Currently, ERM enables data interoperability in AI by providing standardized, machine-readable descriptions that allow diverse systems to exchange and interpret data consistently. As many organisations familiar with, the metadata schemas like Dublin Core, Schema.org, and FAIR data principles help align structure and semantics across datasets are supporting seamless integration in distributed AI environments (Wilkinson et al., 2016; Barone et al., 2017). Moreover, according to Peng (2011) & Tenopir et al. (2011), the interoperability could ensure that AI models trained on multiple sources of data can accurately interpret and use inputs regardless of origin, format, or platform. In fact, by referring to Gollins et al. (2015), AI systems have scale globally, interoperable metadata enhances cross domain collaboration, reduces redundancy, and fosters reuse of high-quality of datasets. Therefore, the metadata standardization is a critical to enable the robust and connecting with the AI ecosystems.

2.4 Supporting Ethical and Responsible AI

The existence of many types of AI system has led to the huge number of ERM created. This is where the ERM plays a crucial role in supporting ethical and responsible AI. As to support the ethical and responsible AI execution, it is importance to document the critical information such as data sources, consent terms, collection contexts, and bias indicators. This is also includes allowing the AI developers to assess the ethical implications of training data and model outputs, helping prevent algorithmic discrimination and misuse (Mittelstadt et al., 2016; Veale & Binns, 2017). On the other hand, metadata also facilitates aspect of accountability through enabling the traceability of decisions made by AI systems, which is essential for regulatory compliance and public trust (McGregor, Murray, & Ng, 2019; Morley et al., 2021). This is supported by Rahwan (2018) which stated that the importance of embedding ethical metadata. The ethical metadata includes data sensitivity labels or intended use restrictions which could help organisations align with AI development that relates to human rights and social norms. Based on this justification, it is proven that the comprehensive metadata is a cornerstone of transparent and fair could generate a proper responsible AI system.

2.5 Enhancing the Quality of AI Training Data

In today's environment, the ERM significantly enhances the quality of AI training data by providing detailed contextual information to organisations. The information provided includes source reliability, data accuracy, 5696abelling consistency, and collection methods. In ensuring the organisations contain the high quality of metadata, it is importance to ensures the datasets are properly documented, reducing bias, redundancy, or mislabeled entries, which contribute to the major threats on model performance (Gebru et al., 2021; Paullada et al., 2021). Moreover, the dedicated initiatives such as "Datasheets for Datasets" and "Data Statements" are directly promote the standardization of metadata in practice which improve transparency and fairness in AI training (Bender & Friedman, 2018; Holland et al., 2018). This followed by Mitchell et al. (2019) which addressing the metadata also supports versioning and traceability, allowing developers to track updates and ensure model reproducibility are correctly in place. Through these discussions, the metadata is not just a supplementary asset but considered as a critical driver for building quality of AI training data in any forms of applications and systems.

2.6 Ensuring Long-Term Sustainability and Reproducibility

Generally, the requirement of maintaining the ERM in organizations become one of the importance aspects that require proper execution especially when there is involvement of AI. This is because the ERM are vital for ensuring the long-term sustainability and reproducibility of AI systems by preserving essential contextual and technical details about datasets over time. These includes the roles of metadata in recording the version history, licensing information, file formats, and preprocessing steps. Furthermore, this can help the future researchers and developers to understand, reuse, and validate data and models, even after years of storage (Peng, 2021; Yakutovich et al., 2021). Meanwhile, maintaining the metadata could facilitates the reproducibility of AI experiments and supports compliance with open science and FAIR data principles (Wilkinson et al., 2016; Raji et al., 2020). Moreover, metadata aids that being used in maintaining the legacy AI systems applicable and executed properly by documenting dependencies, hardware environments, and parameter settings (Chard et al., 2022). Therefore, through the entire explanation, the robust metadata infrastructures are foundational to sustaining transparent, replicable, and reliable AI research especially in long term usage.

Overall, the literature gathered through several scholars' explanation shows that the roles of ERM on AI growth is purely importance specifically for improving the AI usage. The AI is not limited to systems, but also on the aspect of applications and data transmission as well. This has been proven to the justification above where the completion of each metadata is stated directly to the aspect of organizations requirement and practice. This is also means that the application of ERM in any AI system in organisations contributes many compensations especially in the aspects of research and development of AI disciplines. Thus, this is also proven by the findings where the relation between ERM and AI are closely related without any argument by the scholars. Therefore, claiming the roles of ERM are perfectly help the growth of AI is sensible and acceptable.

METHODOLOGY

In this study, it being highlighted that the selection of method used in gathering findings from literature is using systematic review technique. This is because systematic review techniques offer robust methods for synthesizing existing research which allows comprehensive and objective analysis for specific topics (Page et al., 2021). According to Higgins et al. (2022), following a structured and transparent process, it can reduce the risk of bias and enhance the reproducibility of findings. This is followed by Tricco et al. (2023) which stated that this type of reviews is essential for informing evidence-based practices which are particularly applied in healthcare and social sciences, where decision making must rely on high quality data. Additionally, systematic reviews help identify knowledge gaps which can set a direction for the future research agendas (Pollock et al., 2022). Thus,

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this could grow the use of technique in policy making and demonstrates the value in translating research into actionable insights (Roehrig et al., 2023).

Based on above discussion, this is completely justified the selection of systematic review in gathering the literature for this study. This is also justified that the systematic review is purely applicable and structured to be used especially in terms of providing solid evidence in resolving any issues faced by the researchers.

FINDINGS

In this section, the overall findings of this paper are presented. In order to easily understand the entire findings gathered through the systematic review technique, the figure below is designed to present the SIX (6) roles of ERM in AI.

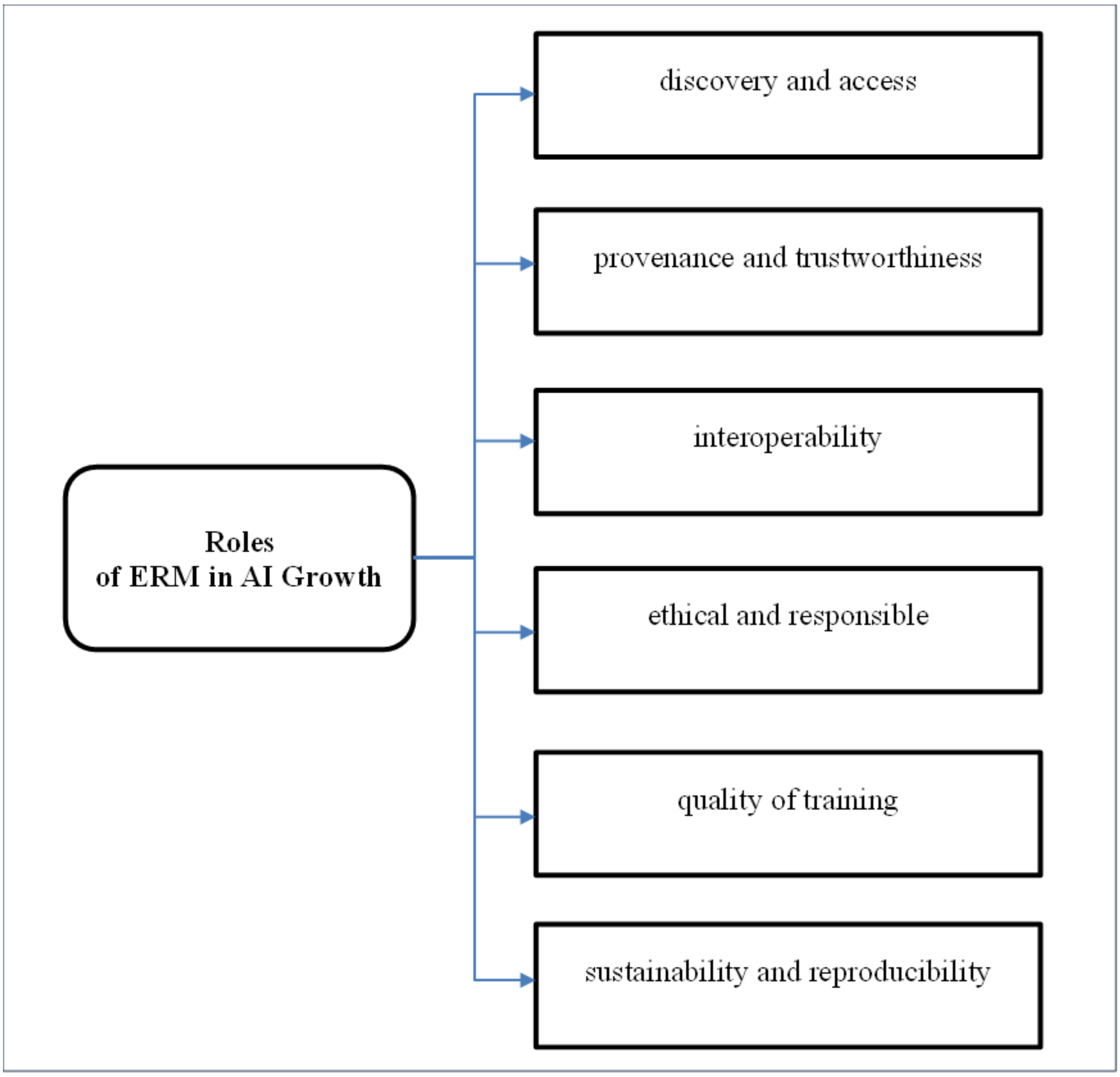

Figure 1. Roles of ERM in AI growth

Based on figure 1 above, there are six (6) roles of ERM in AI growth are identified. There are data "discovery and access", "provenance and trustworthiness", "interoperability", "ethical and responsible AI", "quality of AI Training", and long-term "sustainability and reproducibility". Through this identification, it shows that the ERM contributes a lot in terms of the growth of AI. This is not only focusing on the data or identification of procedures, but it is also focusing on the aspect of sustainability and reproducibility of AI in organisations. Kale et al. (2023) explore how provenance metadata supports explainability, trustworthiness, ethical and responsible AI, and reproducibility. This is also supported by Bernier et al. (2023) in their study, which focused on recording the ethical provenance of data that involves consent and stewardship metadata in promoting ethical and responsible AI.

Furthermore, metadata is key, for example, to provide effective searching for advanced day-to-day tasks (Mosha & Ngulube, 2023), and to provide access controls due to regulatory concerns. (Mosha & Ngulube, 2023). It is also vital to provide accurate descriptive, administrative and structural metadata to help records retain their value, and to remain accessible (Shi et al., 2025). Effective electronic records management and provision requires effective metadata frameworks that can express the provenance, integrity and connections of various digital objects, which allows interoperability across diverse systems (Rolan, 2017). As highlighted by Mannheimer et al. (2024) and Lemieux et al. (2025), there is a need for strong metadata governance and ethical considerations as AI increasingly handles metadata extraction and inference. This trend raises new risks, including privacy breaches.

Sequentially, this also shows ERM is essential to ensure each of the process in AI follow the actual procedures in terms of its implementation activities. This is not limited to the technology only, but it is also important to nurture actual understanding to the staff and stakeholders that involved in AI applications through proper conducted training. Overall, the findings shows that the roles and responsibilities of ERM in AI is very importance. As this firmly proven importance, the roles of ERMS cannot be neglected by the organisation while implementing AI.

CONCLUSION

In conclusion, the ERM and AI growth are proven connected and can generate a proper connection and provide solid evidence on any legal obligations. Embedding the roles of ERM in AI execution on any organisations objectively provides a tremendous outcome in decision making. Using a proper medium and platform, the ERM can perfectly function and executed properly. As ERM need a systems and applications to be operated, the AI application become a support system that can ensure the entire process in organizations meet the organizations objectives. This followed by preserving the entire ERM in AI system as an asset for the future use. The asset of organisations cannot be protected without appropriate ERM implementation. While organisations enable their business using AI as a platform, the outstanding initiatives for preserving the ERM need to be improved. This includes enabling data discovery, ensuring provenance, supporting interoperability, guiding ethical use, enhancing training quality, and ensuring reproducibility, metadata transforms raw data into intelligent, actionable knowledge. However, the initiative could be affected as the AI technology continuously evolved. As AI continues to evolve, future systems will depend not only on big data but also on smart data where the data enriched, structured, and contextualized through ERM need to be in place as well. Thus, the investments in metadata infrastructure, governance, and standards will be key to advancing AI in a sustainable and trustworthy direction and growth.

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