# Charting the Transformation of Enterprise Information Management: AI Explainability and Transparency in EIM Practice

Lufan Zhang[a] and Paul Scifleet[b]
*Swinburne University of Technology, Melbourne, Victoria, Australia*

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Abstract: Today's data-intensive environment poses significant challenges for enterprises in managing their vital information assets that often exceed manual capabilities. Despite a promising potential to assist, there's mistrust and misunderstanding of the values AI presents to Enterprise Information Management. This paper investigates the current state of AI-led changes to EIM practices and proposes an approach to improve understanding of AI's transformative role and impact on EIM. By charting AI use in EIM platforms across five areas - AI development, AI techniques, AI-integrated EIM capabilities, AI applications, and AI impacts – along with practice-based criteria for evaluating AI-integrated EIM solutions, this paper lays the foundation for explainable and transparent AI in EIM.

## 1 INTRODUCTION

In the current massive data environment enterprises face substantial challenges in managing their most vital information resources. The last decade has generated more data, documents and records than any previous decade of human activity, however most information resources remain predominantly unstructured and poorly controlled (Kolandaisamy et al., 2024), making them less reliable, retrievable, and accessible than ever before (Jaillant, 2022). The overwhelming volume of information is exceeding in-house expertise and the manual or semi-automated approaches that most enterprises usually take to implement architectures for information control. Consequently, it is not surprising to see increasing attention being paid to applying Artificial Intelligence (AI) and Machine Learning (ML) based solutions in Enterprise Information Management (EIM) (Baviskar et al., 2021) including for, the classification of digital assets (Huddart, 2022), authoritative records control, taxonomy and metadata management (Duranti et al., 2022), and screening for sensitive and confidential information communicated via email (Schneider et al., 2019).

Despite the promising potential of AI-based approaches to enterprises' IM needs, current evidence indicates that the inherent complexity and opacity of AI cause mistrust and misunderstanding among EIM practitioners about the transformational opportunities and value AI presents (Adadi & Berrada, 2018). While explainable AI (XAI) research initiatives aim to improve the transparency and understandability of complex AI solutions for end users, these approaches are primarily algorithm-centric and highly technical, often falling short in adequately addressing the needs of non-expert users (Barredo Arrieta et al., 2020). In contrast to the AI experts, programmers, and data analysts, who typically interact with AI at algorithm and model design levels (Bunn, 2020; Langer et al., 2021), EIM practitioners do not need to understand AI algorithm functions and the reasons behind the generation of specific outcomes. Their first experience of AI is often through interface interactions. This might involve experimenting with publicly available tools like ChatGPT or investigating the use of AI product integration in other workplace tools. EIM professionals are more concerned with the practical applications and utility of AI across the information management lifecycle (Haresamudram et al., 2023). Solutions based on an *explainable AI in the context of EIM* are required to meet the practical

[a] https://orcid.org/0009-0004-5148-564X
[b] https://orcid.org/0000-0003-2776-1742



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needs and interests of IM practitioners. To address this need, this study investigates the current state of AI use in EIM systems and the changes this is bringing to information management practice, this paper presents the findings from an environmental scan of AI integration into EIM platforms, focusing on how understandable new AI-based solutions are for practitioners and, on the characteristics required for explainable AI in EIM.

The research findings present current issues and challenges in EIM as prioritised by 20 leading EIM platform providers between August 2022 and November 2023. Research outcomes include the categorisation of AI use by platforms into five areas required to support the explainability and understandability of AI for practitioners seeking to adopt new approaches. These include describing 1) how *AI development* is taking shape, 2) what underlying *AI techniques are being used*, 3) how *AI integration* maps to *EIM capabilities*, 4) what *AI applications* are available for use, and 5) how *AI impacts* on EIM practices. Moreover, to evaluate the extent to which information provided by the 20 AI-integrated EIM platforms is clear and transparent for practitioners, an outcome of this research is a model for evaluating AI transparency in EIM based on six practical criteria: *1) Provision of AI development details 2) Provision of AI function details 3) Provision of AI impacts (benefits & risks) 4) Provision of real-world use cases 5) User experience design for AI-integrated interface 6) Human-AI interaction.*

The contribution of the research is twofold. Firstly, it adds to knowledge in EIM by uncovering the role and impact of AI in EIM practices, with five practice-based categories to improve the description and understanding of AI integration in EIM recommended. This offers a practical contribution for EIM practitioners seeking to leverage AI in their work, and is supported by a further six criteria for AI transparency, developed as an outcome of this research, that both vendors and practitioners can work towards achieving. Both contribute to the field of Explainable AI by addressing the needs of non-experts seeking to work with AI and, through this, promoting human agency in explainable AI (XAI).

The following sections of the paper discuss key topics in related research, followed by an elaboration of the research design and findings. The paper then concludes with a discussion of the current state of AI-led changes in EIM practices and reflects on how AI-integrated EIM practices can be facilitated.

# 2 RELATED WORK

## 2.1 EIM Issues and Challenges

Enterprise Information Management is an overarching concept that encompasses a range of related information systems and information management work practices including Enterprise Content Management (ECM), Electronic Records Management (ERM), Document Management (DM), and Knowledge Management (KM) (AIIM, 2024). Notably, these terms are often used interchangeably in industry (Scifleet et al., 2023). EIM can be broadly defined as the integrated, enterprise-wide, strategic management of all types (physical, digital, differing sources and formats) of enterprise information assets over their entire lifecycle of business use (Jaakonmäki et al., 2018; Williams et al., 2014). The term *information asset* encompasses all data, information, documents, and records required for the everyday work practices of business (Scifleet et al. 2023). Hausmann et al.'s research on enterprise information readiness further summarises EIM as a comprehensive initiative for managing information assets throughout the entire lifecycle to unlock value, with a focus on ensuring regulatory compliance. A key goal is to eliminate information silos across business departments and areas of work, ensuring the availability of well-structured information when needed (Hausmann et al., 2014).

Notably, many of the EIM issues identified for business in an industry survey by Hausmann and Williams et al. in 2014 remain relevant (Hausmann et al., 2014; Williams et al., 2014), if not more pronounced following a survey conducted a decade later (Scifleet et al. 2023). Hausmann et al., (2014) identified the challenges for practitioners in managing an increased volume and variety of business information and prioritised compliance and assurance as central with new technologies and new types of data, such as social media impacting businesses. Both the 2014 and 2023 survey results revealed that while enterprises self-rated highly in achieving conformance goals, they continued to struggle when working with information to achieve performance objectives requiring timely access to critical information, sharing information (both internally and externally), managing the information lifecycle, deriving value from, and delivering actionable business intelligence (Hausmann et al., 2014; Scifleet et al., 2023; Williams et al., 2014). Additionally, the 2023 survey highlights the compounding and negative effect of an overwhelming growth in employee-created data through an increasing number of applications.

In this research, we have built from the many well-known challenges presented by Hausmann et al (2014) and others to revisit priorities current in practice today: with a focus on the role that platform providers can play by providing advanced, transparent, understandable and usable AI-based solutions for acquiring, organizing, storing, retrieving, and sharing information assets within an organization. EIM systems are beginning to integrate AI across areas of information management that are traditionally labour-intensive and hard to achieve, e.g. taxonomy development, classification, process automation, search and findability (Duranti et al., 2022). Despite the promising features that AI can bring to the EIM space, we still lack a holistic understanding of how AI is positioned in EIM practice. Understanding the steps that are being undertaken to achieve AI integration and transform EIM practice is a critical area for research.

## 2.2 AI and ML in the EIM Context

Within the EIM field, we have found the term *Artificial Intelligence (AI)* serving as an overarching concept encapsulating many aspects of cognitive computing and advanced programming aimed at performing tasks that typically require human intelligence, though in most cases it is being used to describe narrow, task-specific uses of AI (Meske et al., 2022). As a subset of AI, *Machine Learning (ML)* specifically focuses on developing algorithms and models that enable computers to learn from data, allowing them to undertake information processing to deliver outputs and make predictions, or decisions, without the need for additional explicit human programming or human intervention (Barredo Arrieta et al., 2020). Martens and Provost (2014) have demonstrated how ML can be applied to document classification tasks by selecting a minimal set of words to successfully classify document features for management purposes. In a study by Ragano et al. (2022), semi-supervised ML models were used to evaluate audio quality in digital sound archives, demonstrating potential benefits for other multimedia, such as video calls and streaming services. Sambetbayeva et al. (2022) highlight the document management challenges in the context of the data deluge and propose the use of ML techniques to enhance document retrieval. The potential of AI tools for managing digital records has gained widespread recognition in records management with Duranti et al' (2022) and others highlighting that the requirements for collecting and indexing digital records in a reproducible manner far exceed manual capabilities (Duranti et al., 2022; Schneider et al., 2019). AI technologies, such as Recurrent Neural Networks (RNN) (Shabou et al., 2020), Handwritten Text Recognition (HTR) (Goudarouli et al., 2019), and Chatbots (Gupta & Kapoor, 2020) are all being proposed as means for reducing labour intensive work, increasing efficiency and effectiveness with examples of their role in facilitating record classifications, access to paper-based archival information, and establishing new knowledge available. What is at issue, is just how understandable and useful these technologies are for IM practitioners in everyday work, where they are tasked with explaining application, use, and value to the enterprise?

## 2.3 Explainable AI (XAI) and AI Transparency

The practical implementation of AI and ML in real-world business settings is often met with scepticism by industry professionals (Modiba, 2023). Predominately this scepticism stems from perceptions of AI as an uninterpretable “black box”, with significant concerns about transparency, trustworthiness, and a need to improve understanding of how AI systems produce their outcomes (Adadi & Berrada, 2018). Consequently, there is a growing prioritisation for *Explainable AI (XAI)*, with an overarching goal of improving the accessibility of intelligent systems (Meske et al., 2022). The concept of XAI demands a better explanation about how AI-generated outcomes are achieved. This has resulted in substantial progress within the AI community, where XAI is seen as a sub-field of AI (Adadi & Berrada, 2018; Barredo Arrieta et al., 2020) that aims to provide users with the ability to see inside the black-box. This is typically facilitated through the lens of another algorithm that has the role of describing the logic and decision-making processes of the AI and generating a report that confirms its operations. However, in turning to computational solutions to read an algorithm and and report on the veracity of black-boxed behaviours so that the AI can be trusted, for example in a legal claim, we are at risk of using one opaque method to describe another with little gain for practitioners (Adadi & Berrada, 2018). The Human-Computer Interaction (HCI) community has approached this differently, by bringing a human-centred perspective to XAI that emphasises the significant role of humans in the explanatory process, arguing the importance of being able to engage different user-stakeholder groups and their needs in AI development and use (Meske et al., 2022).

HCI research has focussed on understanding users' perceptions of XAI methods, with research evaluating different HCI-XAI methods for their explanatory capabilities: having the right method in place to explain AI to a user can, in turn, contribute to better more understandable AI systems design (Wang & Yin, 2021; Wanner et al., 2022). Even so, many approaches to XAI still remain technical and often struggle to be translated into practical implementations when it comes to assisting non-expert users in making decisions about AI in work-based contexts (De et al., 2020). The need to improve explainability for non-experts from a practice perspective remains (Brennen, 2020; Bunn, 2020).

EIM practitioners' engagement with AI will be through those tools in EIM platforms that they use to meet their daily information management needs. AI will be assessed on the practical benefits gained. Instead of delving into detailed micro-level explanations of AI models, there is a need to link the *understandability of AI* to EIM practices, with an emphasis on being able to identify and explain system-level applications in AI-integrated EIM transparently, in as open and clear way as possible for practitioners.

AI transparency has been identified as a key requirement for AI technologies by the AI HLEG (the European Commission's High-Level Expert Group on Artificial Intelligence), and the transparency of data processing in AI applications is mandated by the GDPR (General Data Protection Regulation) (Felzmann et al., 2019). Broadly referring to the principle of making AI systems understandable, explainable, and accountable, AI transparency concerns disclosing information about an AI system, typically to support judgments regarding fairness, trustworthiness, safety, efficacy, accountability, and compliance with regulatory and legislative frameworks (Andrada et al., 2023). The problem with AI's "black box" is a clear lack of transparency; however, the concept of AI transparency itself is often opaque (Kiseleva et al., 2022). AI transparency research primarily targets algorithmic transparency, aiming to provide visibility into the underlying algorithms and neural networks to help rationalize the outcomes produced by complex programming (Andrada et al., 2023). However, algorithmic transparency alone does not address the needs of different AI stakeholder groups and thus fails to make AI systems more understandable to non-experts (Felzmann et al., 2019; Haresamudram et al., 2023). To clarify different types of AI transparency and what greater transparency might entail, Andrada et al. (2022) offer a taxonomy that includes two main types of AI transparency: reflective transparency and transparency-in-use. Reflective transparency encompasses information transparency, material transparency, and transformation transparency. Transparency-in-use focuses on ensuring the interface itself is intuitive, allowing users to understand and navigate systems to complete their tasks. Similarly, Haresamudram et al. (2023) have proposed three levels of transparency relevant to diverse stakeholder groups and contexts: 1) algorithmic transparency, 2) interaction transparency, and 3) social transparency, however the categories remain broad. Despite a better understanding of the different aspects of AI transparency for various stakeholder groups, research on how AI transparency translates into applied settings is limited (Haresamudram et al., 2023). This study addresses the gap by operationalizing AI transparency with the EIM context in mind, providing a set of six practical evaluation criteria for AI transparency.

# 3 RESEARCH METHODOLOGY AND DESIGN

## 3.1 Research Objectives

The integration of AI into EIM platforms will transform information management practice not simply as a by-product of smarter off-the-shelf automation, but because EIM practitioners will adapt to the use of AI by altering the conventions and practical knowledge of everyday work in EIM, and by contributing to the design of AI solutions specific to EIM (De Certeau & Mayol, 1998) (Fensham et al., 2020). This research then, contributes to an improved understanding of the transformative role of AI and its impact by investigating the current state of AI-led changes to practice and presents the foundations for a practice-based descriptive framework for explainable and transparent AI in EIM. The approach taken is based on a sociotechnical and practice theory perspective (Orlikowski & Scott, 2016), holding the viewpoint that both people (the practitioners) and technologies (the platforms) have the agency to influence and shape each other, and addresses the following research objectives (RO) and questions (RQ):

RO1 – To understand current EIM challenges faced by practitioners in the massive data environment.

- RQ1(a) What current EIM issues are faced by practitioners?
- RQ1(b) How are the issues in EIM practice being presented by platform vendors?

RO2 – To describe how AI is being brought into EIM practice by EIM platforms.

- RQ2(a) How is AI for EIM being developed and integrated into platforms?
- RQ2(b) What are the impacts, benefits, and advantages that AI is having on the delivery of EIM services?

RO3 – To devise a working definition of AI explainability and transparency for AI-integrated EIM practices and evaluate the understandability of AI-led changes in EIM platforms.

- RQ3(a) What does AI explainability and transparency mean in applied EIM contexts?
- RQ3(b) How transparent is the information provided by the platforms regarding AI applications?

## 3.2 Research Design

This study's approach is qualitative and based on the environmental scanning (ES) of publicly available Web resources to establish awareness of products, services and strategies constituting the relatively new and emergent delivery of AI in EIM platforms. ES, which has its roots in business analysis, is a method applied by researchers to gather and analyse information concerning the domain of interest from publicly available resources to establish situational awareness of the environment and plan actions accordingly (Auster & Choo, 1994; Zhang et al., 2011). While initially applied by businesses for strategic purposes there has been a shift in the use of ES in recent years to academic research, where the identification and analysis of current, publicly available information resources is critical to research domain awareness (Lau et al., 2020; Yin et al., 2021). As the AI-based changes that are taking place in EIM are arriving from vendors integrating AI into their platforms as products for clients, scanning publicly available information from vendors' websites provides this study with a method appropriate for establishing domain awareness and a starting point for understanding the changes that AI integration in EIM brings.

Data collection for the environmental scan was undertaken in two stages between August 2022 and October 2023, following a series of steps outlined for qualitative media analysis (Altheide & Schneider, 2013), depicted in Figure 1.

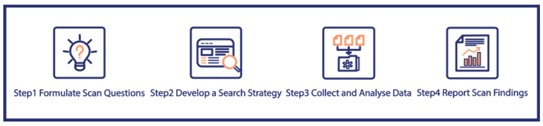


Figure 1: Steps in Environmental Scanning.

Stage one resulted in data collection from 28 leading EIM platforms between August - September 2022, with stage two following in August- October 2023 concentrating on a subset of 20 EIM platforms that were identified from the first stage, because of their more focused discussion of AI integration. While not initially planned for, this allowed the research to map a significant industry change corresponding to the public release of ChatGPT and other OpenAI initiatives from November 2022 (OpenAI, 2022), with a burst of discussion about AI and AI impacts taking place in EIM following ChatGPT hype.

***Steps 1 & 2 Scan Questions and Search Strategy***

Starting an environmental scan involves initiating a search strategy that is based on the research questions. To locate relevant vendors, platforms and service providers, we applied a search strategy comprising broad terms, main terms and related terms, relevant to the focus. Undertaking a Google search with the broadest concepts first, including information management, information management services and information management service providers. The same approach was taken for closely related service areas of, content management, document management, records management and knowledge management.

Following initial search results, information was collected from 140 pages, with the scan identifying more than 70 EM companies including 42 service providers and 28 platform providers. We consider EIM platform providers to be companies that design, develop, and provide integrated technology platform solutions (all software, database, network and cloud components) e.g., OpenText, Oracle NetSuite, Objective, Hyland, Microsoft M365, and EIM service providers as companies who focus on the provision of information management consultancy services, e.g. Access, Astral, TIMG, Cube Records Management, Document Logistix are examples. While EIM service providers also undertake software development to further customise major platforms for clients, they are not platform developers. For the purposes of this study, our starting point to examining changes in practice is the arrival of AI in EIM platforms.

We next focussed on applying inclusion and exclusion criteria to refine the list of EIM platform providers to a list of platforms with Web resources describing explicitly, the incorporation of AI into their offerings. As a result, a pool of 20 AI-integrated EIM vendor platforms was selected for further data collection and analysis

***Steps 3 & 4 Data Collection, Analysis and Reporting***

The unit of analysis for the study comprised three main components of information typically available at each of EIM platforms' websites: 1) platform overviews, 2) AI feature descriptions, and 3) real-world AI-based case studies. The presence of real-world AI-based case studies showcased by the vendors serves as a significant indicator of AI transparency, by describing real EIM use cases for AI.

A "three-level" data collection strategy was implemented for collecting data from the vendors. Navigating "three-levels deep" from the platform overview page ensured that data collection was independent from the platform's website homepage and architecture and helped to locate the same type of information consistently. The "three-levels" are defined as: Level 1, providing an overview of the EIM platform; Level 2, offering a general insight into AI features; and Level 3, providing specific details about AI features. A data collection template was used to ensure the same details were collected for each platform including, platform provider name, platform name, collection date, URLs, platform overview, AI feature descriptions, and the presence of real-world AI-based case studies. The raw data collected for each vendor was initially saved to a Word document using the template and then imported into NVivo for further analysis. Excel has been used for supporting analysis and to assist in the visual presentation of the findings.

Thematic content analysis was used to analyse the collected data, following an inductive, ground-up approach in NVivo while acknowledging that the starting questions and topics have framed the analysis (Williamson & Johanson, 2018). The coding process commenced without preconceived categories or themes about AI integration in EIM; instead, the AI-specific categories presented emerged from the research findings during coding. This was supported by sense-making and fact-checking aligned with the current state of cognitive computing, AI, and ML. To ensure reliability, the research team regularly discussed and refined the coding, with inter-coder reliability checks conducted to reach consensus on themes, topics, and categories, leading to a rigorous process of topic reduction and confirmation.

# 4 RESULTS

## 4.1 EIM Issues and Challenges

The thematic content analysis identified eight EIM issues for practitioners as described by the 20 EIM platforms: immature digitalisation, information security, privacy, and compliance (ISPC) risk, information silos, poor information findability, information overload, poor information sharing, poor information utilisation, and information quality concerns (Figure 2).

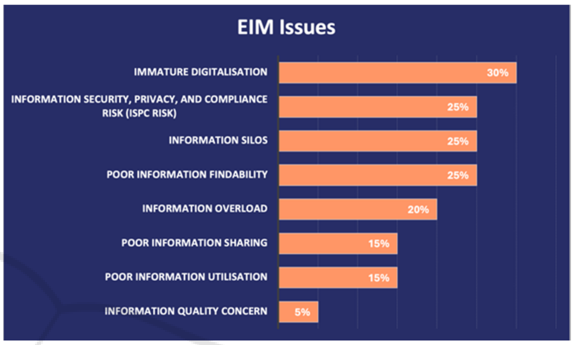


Figure 2: EIM Issues as prioritised by EIM Platforms.

Immature digitalisation (N=6, 30%) refers to lacking sufficient digitalising capabilities to leverage digital technologies for the automation of manual 'paper-driven' processes. Although OCR techniques have been widely utilised for converting documents into digital forms, full automation remains a critical challenge for many enterprises in managing their information assets.

Information security, privacy, and compliance (ISCP) risk (N=5, 25%) refers to the challenges faced by enterprises in meeting information security, privacy and regulatory compliance over their information assets. While flexible and improved collaboration enables better productivity, unauthorised access to information and lack of proper control continue to cause data breaches. Enterprises also raise concerns about identifying and protecting their customers' sensitive and personally identifiable information (PII).

Information silos (N=5, 25%) and poor information findability (N=5, 25%) are closely linked issues that significantly impact information sharing (N=3, 15%). Information silos occur when data is stored in multiple or geographically dispersed locations, with fragmentation resulting from information being spread across different systems, tools, siloed repositories, and disconnected end-line-of-business applications. Siloed information leads to poor information findability, making it difficult for employees to access information when needed. This impacts productivity and hinders both internal and external information sharing, resulting in lower productivity and higher information risks.

Information overload is another critical issue identified (N=4, 20%), that arises from the overwhelming scale of information coming from different sources and channels, and is closely linked, in platform discussion, with poor information utilisation (N=3, 15%). This includes challenges in knowledge discovery and obtaining data-driven business insights.

While not prioritised by EIM platforms (N=1, 5%), information quality concerns must be seen as remaining critical. Enterprises raise concerns about the quality of their information and the trustworthiness of decisions made based on this (Scifleet, 2023). The accuracy and reliability of analytical insights always depend heavily on data quality, and the success of AI projects in enterprises will rely heavily on the quality of the datasets that AI models are trained with.

## 4.2 AI Explainability in EIM Platforms

Table 1 categorises this study's findings across five key areas for explainability (XAI) that practitioners can consider when seeking to understand and evaluate AI use in EIM platforms: AI Development, AI Techniques, AI-integrated EIM Capabilities, AI Applications in EIM, and AI Impacts. These areas support the explainability and understandability of AI applications for EIM practitioners.

Table 1: Five categories of AI use in EIM.

| Category | Definition |
|---|---|
| AI Development | Refers to *the way AI is developed* inhouse or adopted by an EIM platform, to develop specific AI solutions and AI model training. |
| AI Techniques | Refers to *types of approaches* (e.g. computer vision, generative AI, deep learning) employed in EIM platforms' AI offerings. |
| AI-integrated EIM Capabilities | Refers to the *EIM capabilities* for managing enterprise information assets through AI integration, e.g. AI-powered information capture. |
| AI Applications in EIM | Refers to the *underlying AI applications* that support EIM capabilities e.g. Automated data classification, Automated workflows. |
| AI Impacts | Refers to *benefits and advantages* identified for integrating AI into EIM practices across the EIM lifecycle. |

### 4.2.1 AI Development

We consider two sub-categories important as part of AI Development: AI solutions and AI training and deployment. AI solutions refer to the integration of an AI capability directly into an EIM platform either as native AI solutions (developed in-house) or by including third-party AI solutions. Among the 20 platforms analysed, 12 are explicit about how they are developing AI, while 8 are not. That 40% do not share this level of detail remains a significant explainability concern for practitioners. As shown in Figure 3, the majority of the 12 platforms take a Native-AI approach (N=9, 75%) to development. Others adopt a third-party AI solution (N=3, 25%), working with well-known AI service providers, including Clarifai, Microsoft Cognitive Services and OpenAI, to offer AI capabilities to their clients.

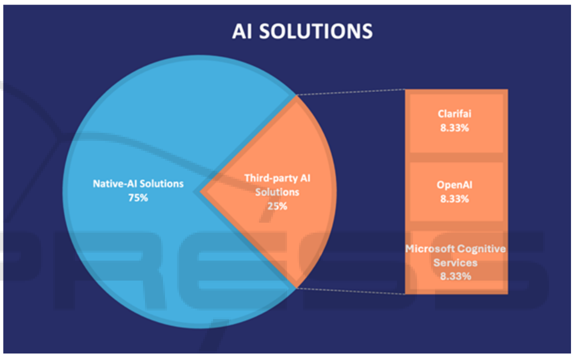


Figure 3: AI Development – AI Solutions.

Training and deployment encompass key aspects of AI model development and use, including data use with AI, human-AI interaction, pre-built AI models, customisation capability, model performance improvement, explainable features, and AI limitations (Figure 4).

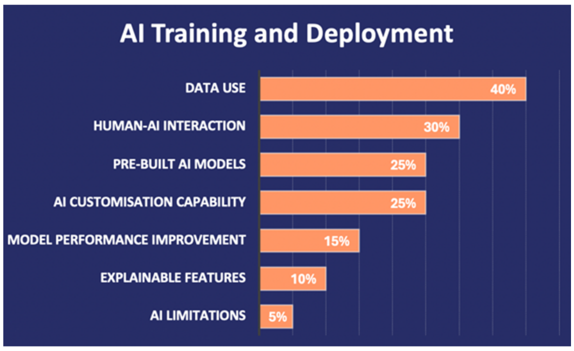


Figure 4: AI Development - AI Training and Deployment.

Data use with AI (N=8, 40%) involves datasets for training AI models and data use by deployed AI products. *Understandability*, about how AI works with data is crucial for addressing concerns regarding the security and sensitivity of proprietary datasets within enterprises. While some platforms clarify that datasets are used with enterprises' consent for model training purposes, concerns remain about the security and sensitivity of data used in deployed AI products.

Human-AI interaction (N=6, 30%) represents a key feature of AI development in the EIM platforms, where the interaction between humans and AI can take various forms. For example, humans can validate AI-produced results and provide corrections or feedback to help AI systems improve continuously.

Pre-built AI models (N=5, 25%) include pre-built or out-of-the-box AI models that are shipped with the platform. Without the burden of undertaking any further development, practitioners can interact with these pre-built AI models at the application level. However, this does not lower the burden for explainability as some platforms offering pre-built AI models also provide AI customisation capabilities (N=5, 25%), allowing integrated AI applications, including AI models and generative AI prompts, to be customised to specific use cases and business needs. The options for customising AI models vary widely, ranging from allowing practitioners to build an AI model from scratch to simply tuning model parameters or selecting from various models or model versions to achieve optimised results. Model performance improvement (N=3, 15%) includes enabling continuous learning capabilities and incorporating human-in-the-loop verification and feedback based on proper business context.

Explainable features and limitations (N=3, 15%) represent features available on EIM platforms that indicate the accuracy and reliability of AI-generated results. For example, platforms provide accuracy rankings for suggested filing locations, or use different colours to indicate certainty levels in indexing. Despite its importance for improving users' trust in AI-generated outputs, only a few platforms offer this. Additionally, only one platform in our analysis acknowledges the limitations of AI applications, noting that AI performance relies heavily on the quality of the training data used.

### 4.2.2 AI Techniques

Seven significant sub-categories of AI techniques emerged from the content analysis: Advanced Character Recognition (ACR), Generative AI, AI-integrated Robotic Process Automation (RPA), Computer Vision, Natural Language Processing (NLP), Deep Learning, and Generic AI and ML (Figure 5).

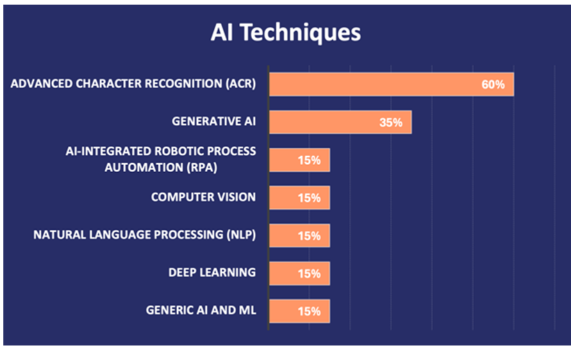


Figure 5: AI Techniques.

Among the seven main categories emerged from AI techniques, it is not surprising that Advanced Character Recognition (ACR) (N=12, 60%) appears to be the most employed AI technique in the solutions offered by EIM platforms. With a long history of using OCR for information capture in EIM, ACR is familiar to practitioners. ACR applies AI in various character recognition technologies including Optical Character Recognition (OCR), Intelligent Character Recognition (ICR), and Zonal OCR. These technologies identify and extract text from images, scanned documents, or other visual sources, converting it into editable, searchable text with high accuracy and efficiency.

The second-ranked AI technique making its way in EIM is Generative AI (N=7, 35%), including large language models (LLMs) and generative AI-based chatbots. Since OpenAI released ChatGPT in November 2022, generative AI has significantly changed the way AI tools are thought about for work tasks and are now serving multiple purposes such as generating text, images, and audio and videos. The integration of generative AI chatbots in EIM platforms is transforming EIM practices, including search and retrieval, knowledge-based reporting and digital asset management.

Other underlying AI techniques that are being brought to EIM include AI-integrated Robotic Process Automation (RPA), Computer Vision, Natural Language Processing (NLP), and Deep Learning. While disclosing information about these AI techniques across the platforms provides some transparency for practitioners, details can be dense in terms of applying specific AI techniques across the EIM Lifecycle to improve understandability. Adding to this problem, we found that some platforms are using generic AI and ML terms (N=3, 15%) without explanation, providing no useful information to help practitioners determine the use of these tools for specific IM needs.

### 4.2.3 AI-Integrated EIM Capabilities

Six sub-categories of EIM capabilities that result from AI inclusions were identified from the analysis, we refer to these as AI *powering* of the capability: AI-powered Business Process Automation (BPA), AI-powered Information Capture, AI-powered Information Search and Retrieval, AI-powered Information Security, Privacy and Compliance (ISPC), AI-powered Business Intelligence, and AI-powered eDiscovery (Figure 6).

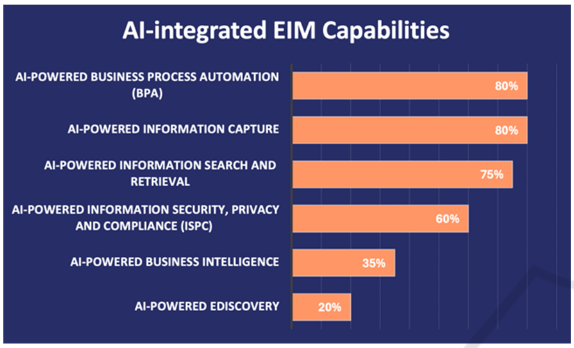


Figure 6: AI-integrated EIM Capabilities.

AI-powered Business Process Automation (BPA) identified across almost all platforms (N=16, 80%), refers to using AI to automate and streamline business processes, e.g. automating repetitive tasks and workflows, and aligns well with the most common EIM issue of immature digitalization, particularly for automating manual processes.

AI-powered Information Capture (N=16, 80%) refers to the application of AI to automate the collection, conversion, organisation and filing of data from source materials. For instance, ACR is often used in AI-powered information capture to process large volumes of scanned paper documents, making them readily available for downstream processing.

AI-powered Information Search and Retrieval (N=15, 75%) involves the application of AI in information search and retrieval processes, including natural language and semantic search across textual, visual, and multimedia data (text, image, video, and audio files). The application of computer vision for image searching is increasing and generative AI-based chatbots are providing new interfaces for employee search queries.

AI-powered Information Security, Privacy, and Compliance (ISPC) (N=12, 60%) involves applying AI to information security, compliance and governance in EIM. This includes applying AI to information security tasks, e.g. detecting threats, and anomalies for data protection. Additionally, AI is utilized for identifying and ranking sensitive and confidential information, including Personally Identifiable Information (PII) and proprietary information. Importantly, AI is being applied in information governance and compliance by automating metadata management and retention and disposal schedules.

AI-powered Business Intelligence (BI) (N=7, 35%) refers to utilising AI for various data analysis and reporting tasks, including relationship analysis, sentiment and behavioural analysis. AI techniques like NLP are used to analyse large volumes of text, identifying relationships across documents and records that are not otherwise apparent.

AI-powered eDiscovery (N=4, 20%) refers to the integration of AI technologies into the process of identifying, preserving, collecting, reviewing, and producing electronically stored information (ESI) for use in legal contexts, e.g. court proceedings, investigations, and other compliance matters. AI can be applied to automate and enhance tasks that would traditionally be time-consuming and labour-intensive, such as identifying required documents based on keywords, concepts, or patterns that occur in a document or even predicting the relevance of documents to a particular court case.

### 4.2.4 AI Applications in EIM

Closely related to AI-integrated EIM capabilities, AI applications in EIM represent the underlying applications of specific AI techniques that support the high-level AI-integrated EIM capabilities. As shown in Figure 7, eight sub-categories emerged from the content analysis: Automated Workflows, Automated Data Classification, Automated Content Creation, Automated Information Recognition, AI Analytics, Help, Assistance and Recommendation Services, Automated Translation and Automated Security Monitoring. Notably, a single AI-integrated EIM capability can be supported by multiple AI applications. For instance, AI-powered information capture is supported by automated information recognition, automated data classification and automated workflows simultaneously, highlighting the complex nature of AI-integrated EIM practices.

Automated workflows (N=18, 90%) are the most common AI applications, where AI is leveraged to automate various workflows, including document workflow and document control workflow. These applications help automate repetitive, manual tasks, allowing employees to focus on higher-priority activities. This aligns with the most common AI-integrated EIM capability: AI-powered Business Process Automation (BPA).

Automated data classification (N=16, 80%) utilizes AI to classify data based on its content, context, or other attributes. This includes tasks such as metadata generation, auto-tagging, auto-indexing, and document classification.

Automated content creation (N=15, 75%) uses AI to generate content, including converting paper-based documents into fully searchable digital documents, automatic form creation and completion, document summarization for reporting and knowledge creation, transcript generation from speech to text, and alt text generation for images.

Automated Information Recognition (N=13, 65%) uses AI to identify information or patterns, such as passport numbers, phone numbers, or driver's licenses from documents. This includes tasks like data extraction and data validation.

AI Analytics (N=8, 40%) use AI to derive insights from data and processes, including content analytics (text analytics, image analytics, audio and video analytics), sentiment analytics (intention analysis and behaviour analysis), and process analytics.

Help, Assistance, and Recommendation Services (N=7, 35%) use AI to provide users with various recommendations. This includes suggesting similar assets, recommending file storage options, providing visualization suggestions and offering transformation suggestions.

Automated Translation (N=3, 15%) uses AI to translate text or speech from one language to another. This capability enhances global business reach and information sharing across different languages.

Automated Security Monitoring (N=2, 10%) uses AI to identify and detect anomalies and threats in content, generating timely alerts to users to protect against data loss. This includes tasks such as anomaly and threat detection, security alert generation, and containing data leakage.

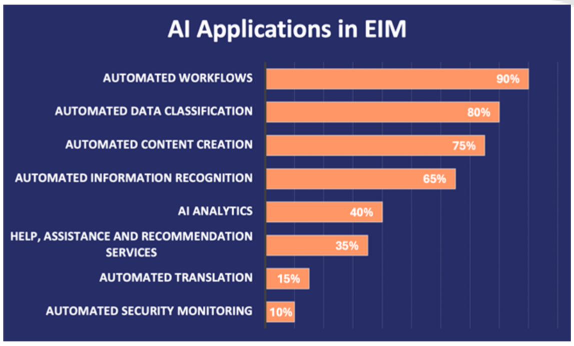


Figure 7: AI Applications in EIM.

### 4.2.5 AI Impacts

Six key categories identifying how AI integration impacts EIM practices were found in the analysis: AI-workplace benefits, AI-enterprise strategic, financial and reputational benefits, AI-user experience benefits, AI-information security, privacy and compliance (ISPC) benefits, AI-information quality improvements, AI-collaboration improvements, AI-customer gains, AI-business sustainability and continuity (Figure 8).

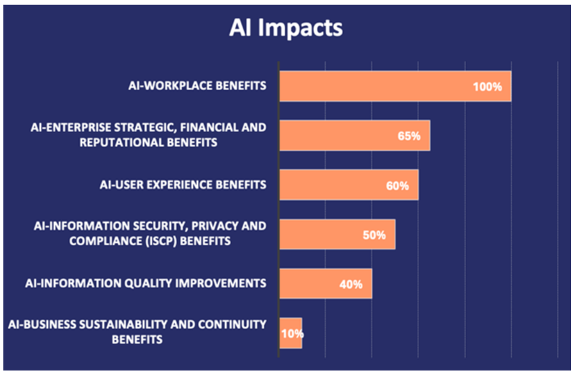


Figure 8: AI Impacts on EIM Practices.

Among these, AI workplace benefits (N=20, 100%) stand out prominently as advantages described across all EIM platforms, including operational benefits, collaboration improvements and employee gains. This aligns with a commonly listed value proposition for AI, that it enhances business operations and employee performance. Associated with this, AI-Enterprise strategic, financial and reputational benefits (N=13, 65%) feature highly, including strategic perspective (greater competitive advantage, more informed decision-making, and richer business insights for uncovering new business opportunities), financial perspective (costsaving and increased ROI), and reputational perspective (brand consistency, cohesive and unified brand experience and customer gains).

AI-user experience benefits (N=12, 60%) centre around a user-friendly including natural language interfaces, no-code environments, reduced dependency on technical expertise, user autonomy, and self-sufficiency, collectively enhancing the ease of AI adoption for users. However, the connection between both workplace and user benefits to AI technology is rarely clearly presented.

AI-Information security, privacy and compliance benefits (N=10, 50%) include enhanced information security, data loss protection, privacy, compliance and regulation adherence, and governance. AI-Information Quality Improvements (N=8, 40%) refers to the improvements regarding to all aspects of Information quality, including integrity, accuracy of data, completeness of data, reduced data errors, and more.

## 4.3 AI Transparency in EIM

Based on the findings and literature, this study proposes that a contextual working definition of *AI transparency* in EIM that enables the evaluation of transparency in AI-integrated EIM offerings is needed. Critically we find that AI Transparency in EIM solutions must encompass *information transparency* (disclosing information relevant to EIM practitioners) and *transparency-in-use* (intuitive user interface and human in the loop) to enable a better explainability: for understanding, trust and adoption of AI applications for EIM practitioners, and note the interdependency in these concepts.

### 4.3.1 AI Transparency Evaluation

To apply AI transparency in EIM, this study has developed six practice-based evaluation criteria that can be used by practitioners: *information transparency* – 1) Provision of AI development details (AI development and AI techniques), 2) Provision of AI function details (AI-integrated EIM Capabilities and AI applications), 3) Provision of AI impacts (Benefits & Risks), 4) Provision of real-world use cases, and *transparency-in-use* – 5) User experience design for AI-integrated interface, 6) Human-AI interaction.

Table 2 evaluates the transparency of current AI-integrated EIM solutions across the 20 platforms in this study, based on these criteria [1]. In terms of information transparency, all platforms offer insights into how AI can support EIM capabilities and the benefits it brings to EIM practices. However, information regarding AI development and the underlying AI techniques used is not fully disclosed, with only a few platforms providing details regarding data use with AI, including how datasets are utilised in AI model training or operational deployments. This lack of transparency on critical technical aspects such as AI techniques and data handling, can raise significant concerns for practitioners, particularly around security, trust and AI adoption in EIM.

Notably, AI risk and proven AI success use cases in the real world are rarely provided by platforms, which can hinder the trust and adoption of AI-integrated EIM offerings among practitioners. Additionally, while most platforms highlight benefits like intuitive, user-friendly interface designs for practitioners to work with their AI products, there is a lack of clarity regarding how humans can align AI with their work practice.

[1] Platform vendors are not identified by name in the Table 2, details can be provided by the authors on application.

# 5 CONCLUSION

## 5.1 Discussion of Findings

Through an environmental scan of 20 leading EIM vendor platforms, this study identified eight interrelated EIM workplace challenges prioritised by the platforms. Compared to the EIM challenges faced by enterprises a decade ago, these issues remain unresolved, if not more problematic. With the emergence and widespread use of generative AI, there EIM systems are turning to AI to address these challenges.

To understand how AI is transforming EIM practices, this study starts by examining what is available to practitioners, charting the role and impact of AI across five areas: AI development, AI techniques, AI-integrated EIM capabilities, AI applications, and AI impacts. EIM platforms are adopting a native-AI approach and developing AI capabilities internally and this is likely to result in a good fit-for-purpose. However, there is a clear lack of information available to support the understandability of AI's role across the information management lifecycle and this needs to be addressed.

Regarding AI-EIM capabilities and integration into practice; AI-powered information capture, search, and retrieval, supporting consistent information filing and organization, enhancing the discovery, sharing, and use of information, and AI-powered business process automation are all extremely promising. AI integration aims to facilitate automated security monitoring and help address compliance risks. In the face of information overload and information silos, generative AI is valuable for extracting relevant information and curating knowledge tailored to practitioners' needs. However, the risks associated with AI use are rarely mentioned.

## 5.2 AI Explainability and Transparency in EIM

The study's findings address the need for contextualized AI explainability and transparency in EIM, and, in addition to developing evaluative categories for understanding AI, we have presented a working definition of AI transparency for EIM practitioners with six criteria covering *information transparency* and *transparency-in-use* available for consideration. By evaluating the transparency of AI-integrated EIM solutions offered by vendor platforms

(Table 2), we find that AI transparency can be improved to facilitate explainability and understanding, trust, and adoption of AI by practitioners. When working with AI, practitioners might not be interested in all the details but require proven success in real-world scenarios that address similar EIM needs.

Regarding ease of use and confidence in AI-produced outcomes, more transparency is needed about how practitioners can interact with AI. This includes understanding how to determine the accuracy or confidence in the results produced by AI systems and how practitioners can be included in the loop to improve this process.

## 5.3 Limitations and Outlook

There are two limitations to this work. Firstly, the analysis is based on scanning the publicly available information provided on the websites of 20 leading EIM platforms. Both the size of the sample and the information sourced are limited. Future work may incorporate more public discourse on AI-integrated EIM offerings, such as industry reports and platform blogs, to achieve a more comprehensive analysis. Secondly, while this study explains the need for contextualized AI transparency *for EIM practitioners* and proposes a working definition of AI explainability and transparency with evaluation criteria, more work is needed to verify these criteria *with EIM practitioners*. That constitutes the second stage of this study. Practitioner interviews have been completed and will be reported at a later stage. This research takes the first step towards making AI applications more understandable, explainable, and transparent in EIM. This work also contributes to the field of Explainable AI by addressing the needs of non-experts in applying and working with AI, thereby promoting human agency in explainable AI (XAI) initiatives.

Table 2: Evaluation of AI transparency in EIM.

| **Transparency Evaluation criteria** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Information Transparency | | | | | | Transparency-in-use | |
| # Platform | 1) Provision of AI development details | | 2) Provision of AI function details | 3) Provision of AI impacts | | 4) Provision of real-world use cases | 5) User experience design for AI-integrated interface | 6) Human-AI interaction |
| | AI Development | AI Techniques | | AI Benefits | AI Risk | | | |
| #1 | √ | √ | √ | √ | | | √ | |
| #2 | | √ | √ | √ | | | | |
| #3 | √ | | √ | √ | | | √ | √ |
| #4 | | √ | √ | √ | | | √ | |
| #5 | | √ | √ | √ | | | √ | |
| #6 | | | √ | √ | | | | |
| #7 | √ | √ | √ | √ | | √ | √ | √ |
| #8 | √ | √ | √ | √ | | √ | √ | |
| #9 | √ | | √ | √ | | √ | | |
| #10 | √ | √ | √ | √ | | | | |
| #11 | √ | √ | √ | √ | √ | | √ | √ |
| #12 | | √ | √ | √ | | | √ | |
| #13 | √ | √ | √ | √ | | | | |
| #14 | √ | √ | √ | √ | | √ | √ | |
| #15 | √ | √ | √ | √ | | √ | | |
| #16 | √ | √ | √ | √ | | | √ | √ |
| #17 | √ | √ | √ | √ | | | √ | |
| #18 | √ | √ | √ | √ | | | | |
| #19 | √ | √ | √ | √ | | √ | √ | √ |
| #20 | √ | √ | √ | √ | | | | √ |

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