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Ontology based mapping of HERM

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Abstract

Enterprise Architecture Management (EAM) provides structured methodologies for planning and analyzing complex organizational ecosystems. One such ecosystem is the German educational system, which spans lifelong learning from kindergarten and school to vocational training, higher education, and professional development. Building integrated digital platforms within this system requires a multi-dimensional perspective on organizational capabilities, data, applications, and technologies. In higher education, the Higher Education Reference Models (HERM) serve as a structured repository of a suitable and domain-specific terminology. However, manually aligning real-world educational scenarios with HERM's about 600 terms is both labor-intensive and potentially inconsistent. This paper presents an automated mapping approach based on a Hybrid Artificial Intelligence (HAI) method, combining Semantic Web technologies, symbolic AI, and NLP-driven extraction. We applied this approach to 50 user scenarios from the prototype project (Bildungsraum Digital, BIRD) of the German National Education Platform, generating structured mappings between user interactions and HERM's core frameworks. The results demonstrate a scalable, transparent method for automated ontology-based scenario analysis, offering a foundation for deep-dive analytics in EAM.

Keywords: Ontology Mapping, Hybrid Artificial Intelligence (HAI), Semantic Web, Enterprise Architecture, Higher Education Reference Models (HERM), Natural Language Processing, Automated Semantic Alignment, Explainable AI (xAI)

1 Introduction

Enterprise Architecture Management (EAM) is of particular significance in the structuring and communication of complex organisational landscapes. By providing an abstracted, high-level representation, EAM enables institutions to navigate the intricate process of local modelling while

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maintaining a coherent global overview. Achieving the right balance between localised detail and overarching structure is essential for strategic decision-making and long-term institutional development, e.g., the digital transformation (Gomes et al., 2020; von der Heyde et al., 2025).

In the context of Higher Education Institutions (HEIs), the Higher Education Reference Model (HERM) curated by CAUDIT (CAUDIT, 2024) has recently emerged as the predominant Enterprise Architecture Management (EAM) reference model (Lethbridge & Alghamdi, 2019; Ferrell et al., 2022; Le Strat et al., 2022; Nauwerck et al., 2022). With adoption by over 1,000 institutions worldwide[3] HERM has proven to be a valuable framework for structuring and managing higher education enterprises. Its international applicability and widespread acceptance underscore its effectiveness in standardising architectural practices across otherwise diverse educational organisations.

However, despite the benefits of EAM and HERM, initialising work with these frameworks remains a significant challenge (Ferrell & Hillicks, 2013; Sanchez-Puchol et al., 2017). Many HEIs struggle with the initial setup and integration of EAM practices into their organisational processes (Syynimaa, 2015; Alghamdi, 2021). To address this, various recommendations have been proposed (Hartmann & von der Heyde, 2025), and dedicated workgroups have been established to facilitate knowledge exchange and best practices (Dei et al., 2020; Maltusch et al., 2025). These initiatives aim to lower the entry barrier for institutions looking to leverage EAM methodologies effectively.

A key issue that has been identified in a number of projects is the creation and maintenance of a preliminary or continuous architectural overview (Bourmpoulias & Tarabanis, 2020). The establishment of a structured and up-to-date view of an institution's enterprise architecture has been identified as a persistent challenge (Guerreiro & Sousa, 2023). However, it is expected to be a crucial element in the digital transformation of higher education institutions (HEIs) (von der Heyde & Hartmann, 2023; von der Heyde et al., 2025). The aim of this paper is to address these challenges by exploring an ontology-based approach to HERM, leveraging TOGAF principles to enhance the initialization and sustainability of architectural overviews in HEIs. There are two main concerns that we wish to address: Firstly, what is an effective method for generating an initial mapping to a reference model in order to establish a baseline? Secondly, how can we maintain this overview and keep it consistent?

2 Background

Enterprise Architecture Management (EAM) relies on structured reasoning and consistent knowledge representation to generate and maintain organisational overviews. While expert systems and symbolic AI have traditionally provided rule-based approaches, recent advancements in natural language processing (NLP) and large language models (LLMs) have introduced new possibilities and challenges. This chapter explores the foundations of our method, examining expert systems, the limitations of LLMs, and the role of symbolic AI and Semantic Web technologies in ensuring reliable and interpretable mappings to reference models like HERM.

2.1 Expert Systems and Symbolic AI

Expert systems were initially developed to enable automated reasoning and support decision-making through rule-based logic within well-defined domains. However, their effectiveness was often constrained by the complexity of encoding expert knowledge and handling ambiguous or evolving contexts. Early applications of Natural Language Processing (NLP) in expert systems

[3] see https://www.caudit.edu.au/communities/caudit-higher-education-reference-models/

remained limited to narrow domains, where predefined rules and structured data allowed only basic forms of automated interpretation.

Symbolic AI builds on similar rule-based principles but extends them through formal logic, ontologies and structured knowledge representation. Unlike expert systems, which typically rely on predefined if-then rules, symbolic AI enables more flexible reasoning by modelling relationships between concepts. In the context of EAM, symbolic AI facilitates clear mappings between institutional structures and reference models like HERM, ensuring consistency and interpretability. In contrast to large language models (LLMs), which generate probabilistic responses, symbolic AI produces deterministic outputs, making it a more reliable foundation for structured enterprise knowledge systems.

2.2 Large Language Models (LLMs)

Recent advancements in large language models (LLMs) have led to a significant improvement of natural language processing (NLP) and expansion in the use of generative AI across various domains. However, despite their impressive capabilities, LLMs demonstrate certain limitations that hinder their application in structured enterprise environments such as Enterprise Architecture Management (EAM).

- **Maintaining Scope:** They are unable to maintain accuracy when responding to queries involving more than 3–5, at most 8, key terms. Beyond this threshold, generated responses tend to become generic or lose contextual precision.
- **Reference Consistency:** Maintaining references to specific terms over extended dialogues is challenging, with the result that terms introduced earlier in a discussion may be misrepresented or entirely lost in later responses.
- **Contextual Differentiation:** When dealing with structured documents, such as reports with multiple subchapters, LLMs often fail to distinguish the necessary focus between different sections, leading to inconsistent emphasis or misinterpretation of key points.
- **Hallucinations:** As LLMs produce the generative AI output based on a stochastic concept, hallucinations remain a challenge and are therefore unreliable as a standalone source for critical decision-making. Without verifiable references, automated outputs cannot be trusted in structured EA models.

2.3 Semantic Web

The Semantic Web extends traditional web technologies by incorporating structured data and ontologies, enabling machine-readable knowledge representation. In EAM, leveraging Semantic Web technologies allows for:

- **Ontology-based modeling:** Formalizing the relationships between enterprise concepts and reference models like HERM.
- **Interoperability:** Ensuring that different systems and institutions can exchange and interpret structured data in a standardized way.
- **Automated reasoning:** Enhancing decision support by enabling inference over structured knowledge representations.

Further possibilities, current open questions and comparisons between different approaches are discussed in the context of structured knowledge extraction for legal test in a comprehensive literature review (Soavi et al. 2022).

3 Hybrid AI Approach

By integrating symbolic AI, Semantic Web technologies, and structured NLP, our Hybrid AI approach leverages the strengths of multiple AI methodologies while overcoming the limitations of purely generative AI to effectively support EAM practices through automation. In our approach, we integrate:

- Semantic Web technologies to represent structured knowledge using ontologies in RDF form.
- Symbolic AI is used to enable logical reasoning, such as interval resolution and structural interpretation.
- Large Language Models (LLMs) are employed for natural language processing tasks, such as the extraction of knowledge from unstructured text.
- Statistical methods are employed to ensure stable behaviour and reliable results when working with LLMs.

This combination allows us to systematically analyse large volumes of text, align extracted information with predefined ontologies, and ensure stable and interpretable outputs.

3.1 Prerequisites

Before implementing our Hybrid AI approach, two key elements must be in place. 1) We need an ontology of the domain as a formalised knowledge structure defining the key concepts, relationships, and entities in the area of interest. In our case, we use the TOGAF based HERM ontology (von der Heyde et al., 2025). 2) The relevant source material needs to be provided as documents or texts containing the knowledge to be analysed and extracted, serving as the input for automatic structuring and interpretation.

3.2 Automated Processing Stages

Our method consists of several automated stages to structure the document, analyze, and extract knowledge from documents while ensuring alignment with the reference ontology.

1. Document Structure Analysis

- Extracting the table of contents (if available) to establish a structural overview.
- Identifying document structure elements such as header hierarchies.
- If no structure is found, using an LLM to infer logical subdivisions within the document.
- Generating sub-chapters where applicable based on content patterns detected by the LLM.

2. Ontology Analysis

- Defining key searchable classes within the ontology.
- Identifying class instances and relationships relevant to the domain.
- Structuring ontology elements to guide the extraction process.

3. Focus Heatmap Generation

- Determining which chapters contain the most relevant information for ontology concepts.
- Using Mann–Whitney U tests (Mann & Whitney, 1948) as statistical measures on NLP-based relevance judgements to rank sections based on their potential insights.

4. Class-Reference Extraction

- Identifying references to ontology classes within relevant chapters.
- Extracting contextual knowledge about each class from the text.
- Mapping extracted information to ontology concepts to ensure structured interpretation.

5. Citation Generation
- Extracting stable and verifiable references from the text (e.g., section and line numbers).
- Associating each reference with its corresponding ontology class and document section.
- Ensuring traceability between extracted knowledge and its original source.

6. Citation Validation
- Cross-referencing extracted citations with the ontology class definitions.
- Using statistical stability measures to verify extraction consistency.
- Filtering out uncertain or ambiguous results to improve reliability.

7. Output Generation
- Generate RDF instances representing structured data for further semantic processing.
- Generate Human-readable text reports for citation verification.
- Generate KPI tables summarizing structured insights and metadata for further analysis.

By integrating symbolic AI, semantic reasoning, LLM-driven text processing, and statistical validation, our Hybrid AI approach ensures that extracted knowledge is both interpretable and reliable within the EAM context.

3.3 Implementation

The implementation of our Hybrid AI approach is built using Go (Golang) for efficiency and scalability. We used OpenAI's ChatGPT-4o-mini-2024-07-18 model for the NLP tasks via the API. The structured and well documented processing used a JSON-based data format that is continuously enriched across all previously described processing stages. An iterative data collection scheme enables continuous updates for changes and high parallelism for optimised performance. To ensure efficiency and consistency in the knowledge extracted, we adopted a need-to-know principle (Lastras et al., 2024), invoking the LLM only when its response is expected to influence subsequent results. In terms of efficiency, this on Shannon's (1948) information theory-based schema reduced the number of API calls by approximately four. As ambiguous LLM requests seemed to generate more hallucinations, we specifically and effectively reduced this side effect of generative AI.

4 Field of Application

In order to evaluate the effectiveness of our Hybrid AI approach, we applied it in two different contexts. Firstly, we conducted an initial test using K12 curricula and secondly, we undertook a large-scale analysis within the BIRD project. The initial test highlighted key challenges in automated ontology mapping, while the second demonstrated the practical value of integrating HERM for analysing educational transitions and institutional interfaces.

4.1 K12 Curriculum and Initial Testing

Initial tests were conducted using the K12 Curriculum Ontology (Waitelonis, 2023) and various curricula from different school types and subjects. The goal was to extract structured knowledge and represent it as an RDF instance. However, results often deviated from the original wording, making direct comparisons difficult. Semantic overlap between similar terms in the original K12-curriculum ontology led to high variance in mappings, highlighting the need for citation validation and an iterative, information-driven approach, as presented in this work.

4.2 Application in the BIRD Project

The BIRD project is a nationwide initiative integrating learning applications and administrative processes across the entire educational journey, from kindergarten to lifelong learning (Knoth et al., 2022; Lucke, 2024; Lucke et al., 2025). It does constitute a major challenge in the design and collection of the required metadata (Rörtgen et al., 2023). Following a user-centric design, it generated extensive user stories, particularly for transitions between educational phases and institutions (Erdmann et al., 2023).

In order to analyse technical and organisational interfaces, the HERM framework was selected as the most prominent and accessible as well as structured EAM approach for higher education institutions (Bourmpoulias & Tarabanis, 2020). The hypothesis was that BIRD scenario descriptions could reveal key interfaces in business capabilities, data, applications and technologies of universities based on the four reference models of HERM in the recently released 3.1.0. version.

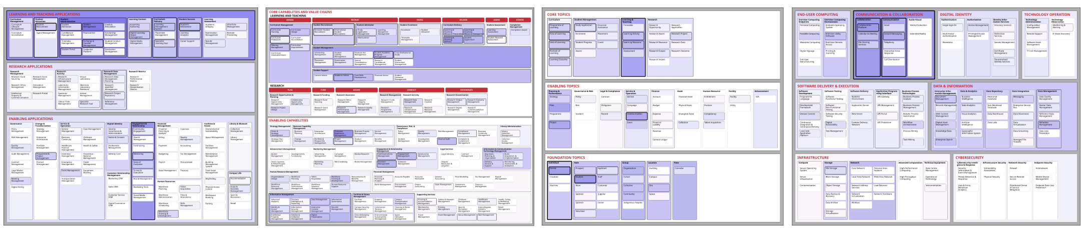

Fig 1: The heatmap illustrates the BIRD Scenario Matching with the HERM. The darker shades of colour indicate a higher number of extractions and validated citations. The thickness of the box frames corresponds to a higher intensity of the terms within the relevant documents. From left to right we see the a) Application Reference Model (ARM), b) Business Capability Reference Model (BRM), c) Data Reference Model (DRM), and d) Technology Reference Model (TRM)

4.3 Results of the automatic mapping

The application of our Hybrid AI approach to the BIRD project posed a substantial technological challenge due to the scale and complexity of the data. The four used higher education reference models comprises 586 terms and definitions, while BIRD encompasses over 50 scenarios (Erdmann et al., 2023), spanning approximately 50 pages of text. Mapping these extensive textual descriptions to a structured reference model necessitated precise handling of semantic similarities and contextual relevance.

To analyse the mapping results, we aggregated the extracted references and visualised them as heatmaps using the SVG tool (von der Heyde, 2022). This provided an intuitive overview of term distribution, highlighting key areas of alignment and divergence between BIRD scenarios and HERM concepts.

As illustrated in Figure 1a, the primary focus of the HEI's applications is student administration, with a particular emphasis on student management and applications for engagement and relationship management. There are extensive references to student recruitment and student advice.

As illustrated in Figure 1b, the focus points align closely with the capabilities outlined in the Business Capability Reference Model (BRM). The primary areas of interest remain the teaching and learning sector, with a particular emphasis on curriculum delivery. Given the nature of the provided material, Customer Experience Management emerges as a significant area of interest. The management of outreach and engagement is also a key priority.

The key aspects identified by applying the HERM Data Reference Model (DRM) to the scenarios are Person, Student, Communication, and Teaching and Learning-based data, e.g. Learning Result (see Figure 1c). Further areas are Plan and Project, as the BIRD platform strongly supports activities using those data types. Learning Resources are detected, but do not constitute a major focal point, which is in alignment with BIRD cataloging and referencing those data. It should be noted that BIRD is not a learning management system containing the data. Several data types of the Curriculum topic are also referred to, as those aspects play a crucial role in the placement of offers.

As outlined in Figure 1d, the Communication and Collaboration areas of the Technology Reference Model (TRM) are displaying the strongest matches, in line with the nature of the BIRD platform prototypes. Intensive matches can be observed in Document Management and Metadata Management applications, which is consistent with the BIRD ecosystem approach.

Figure 2 illustrates the matching for a combination of scenarios from multiple education domains. If the HERM is applicable to K12 in the sense of completeness, it can be deduced from our results that many HEI capabilities are sufficiently similar to be matched by the LLM. The majority of the area shows a reddish tone, indicating equal applicability in K12 and higher education. Tints of purple and blue indicate a stronger match within the higher education sector; orange and yellow indicate a dominance of the K12 sector.

4.4 Shortcomings

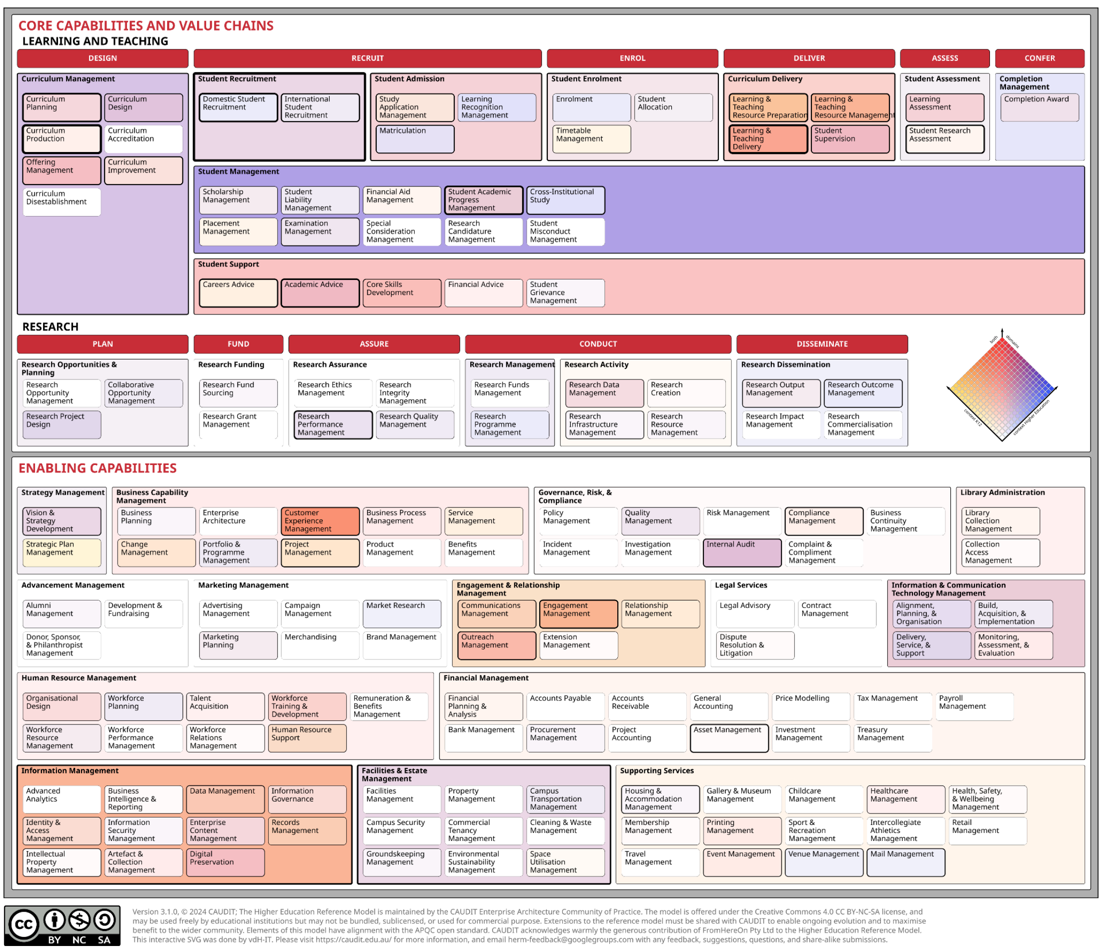

Fig 2: The heatmap illustrates the BIRD Scenario Matching for the K12 and Higher Education Scenario with the HERM Business Capability Reference Model (BRM). The K12 Scenarios are

depicted in Yellow and the Higher Education Scenarios in Blue shading. The mix of both educational domains uses the shading towards Red. The darker shades of colour again indicate a higher number of extractions and validated citations. The thickness of the box frames corresponds to a higher intensity of the terms within the relevant documents.

While the Hybrid AI approach has been successful in automating ontology-based mapping, there are still several limitations that affect its accuracy, interpretability, and generalizability. The system may omit relevant information or overemphasize certain terms, depending on the text structure and LLM responses, which can result in gaps in extracted knowledge or an exaggerated focus on frequently occurring terms from a user perspective. The approach prioritises textual alignment with HERM but does not fully account for institutional variations in how concepts are applied, meaning that organisations may structure capabilities and processes differently, leading to misalignments between extracted mappings and real-world practices. Concepts not explicitly defined in HERM, such as "wallet" in a digital identity context, are ignored or only indirectly mapped. This can result in incomplete representations of certain capabilities, particularly in rapidly evolving digital domains. As the chosen HERM Ontology is specially developed for higher education applying it to K12 education, vocational training or lifelong learning might lead to mismatches and unexpected results. This phenomenon is evident in the alignment of research topics within the school/K12 context. As the approach assumes a higher education-centric perspective ("HEI glasses") and without adapting the ontology, gaps in domain coverage potentially remain.

It is clear that in order to enhance the applicability of this approach across different educational contexts, there is a need for manual oversight, iterative refinement, and potential ontology extensions. In future work, custom domain adaptations and context-aware adjustments should be addressed in order to enhance the robustness and generalizability of the approach.

5 Summary and Outlook

The Hybrid AI approach has shown that combining symbolic AI, LLMs and statistical validation allows for scalable and structured ontology-based mapping. While initial results revealed challenges in terms of semantic consistency and word variation, the iterative, information-driven refinement process significantly improved mapping accuracy. The methodology provides a scalable solution for integrating unstructured text into structured EAM frameworks. As the area of interest is defined by a customer-based ontology, it is a promising tool for future applications in higher education and other sectors. Individual institutions as well as groups of universities could facilitate the identification of potential areas of collaboration by mapping their service landscape on HERM. Overlaps between partners' interests could be visualised and reviewed more easily through interactive heat maps.

In response to user needs and acknowledged shortcomings, future projects will focus on the other educational domains of BIRD (K12, vocational training and lifelong learning). We will therefore apply the hybrid AI to the specific capability models of those domains. We hypothesise that the automatic matching will be able to identify unexpected interfaces between the domains, thus further guiding the design process of the generic architecture in complex projects like BIRD through the artefacts of enterprise architecture practices (Hartmann et al., 2025).

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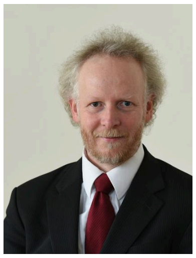

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