RESEARCH PROPOSAL:
Mapping AI in Media: Classifying Products across Production, Broadcast, and Streaming Workflows

Maria Ingold
12693772
Unit 8
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University of Essex Online
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INTRODUCTION

Future Market Insights (2024) predicts that global artificial intelligence (AI) in media and entertainment (M&E) will grow at 17.5% compound annual growth rate (CAGR), from US $10 billion in 2024 to US $51 billion in 2034. McKinsey's (Singla et al., 2024) forecasts even greater impact, estimating that generative AI alone could add US $80-130 billion globally annually in productivity enhancements to M&E.

However, lack of standard definitions for both "AI" and "M&E" means predictions vary and industry-specific insight—for production, broadcast, and streaming workflows—remains too broad. Fragmented proprietary analyses, combined with concerns around intellectual property, ethics, and regulation restricts public discussion.

As a speaker at 19 AI-in-media conferences since 2023, I regularly encountered demand for a consolidated, multi-dimensional, public map of enterprise AI in media products, showing real use cases and strategic value.

AI tool directories such as Future Tools (no date) are too broad and lack industry-validated classification. Ecosystem maps like Omdia's (Deane, 2024) are too narrow and limited to vendor logos. No scalable domain-specific method exists for collating and classifying public AI-for-media products using structured tagging.

PROJECT AIM & OBJECTIVES

This research proposes to address that gap by investigating how public product descriptions can be classified using a structured tagging approach to better understand the role of AI tools in media workflows. The goal is to lay a foundation for further research and analysis.

The project objectives are to:

1. Curate a dataset of publicly listed AI products used in media.
2. Create a tagging structure for consistent product classification.
3. Investigate the use of AI to classify products in the dataset.
4. Evaluate classification performance and analyse patterns.

RESEARCH QUESTIONS

1. What approaches are suitable for tagging and classifying AI-for-media product descriptions?
2. How can these methods be applied in a scalable and consistent way to limited publicly available data?

LITERATURE REVIEW

AI in Media

Google Scholar and Semantic Scholar were used to scope recent academic material relating to AI in media across production, broadcast, and streaming between January 2024 and June 2025. The search excluded concepts like social media, print media, metaverse, and user-generated content. This non-exhaustive exploratory search revealed approximately 170 apparently unique and relevant academic papers, from which a small subset of about 10 were reviewed in more detail to identify themes.

Four initial trends emerged from titles and abstracts: overviews of AI in media, specific use cases, and ethics each accounted for roughly a third, with regulation emerging as a minor theme. While some papers focus on single topics, like Liu (2024) on production, others group a range of applications. For example, Agarwal and Kim (2024, p. 12) categorise AI in media applications into ‘content creation, content distribution, and audience engagement’, while Wang's study (2025, p. 116) addresses ‘content creation, audience engagement, and media management’. Pitoňáková, Pál and Kubala's systemic literature review (2025) centres on content creation and targeted advertising. However, none of these explicitly define specific media sectors, propose a consistent tagging method for AI in media applications, or consistently ground categories with real-world products.

Tagging Approach

In the absence of a formalised AI-in-media tool classification method, this research will investigate structured tagging to enable consistent categorisation, comparison, and analysis. Taheri Moghadam, Hooman and Sheikhtaheri (2022) differentiate between terminology (domain-specific vocabulary), taxonomies (hierarchical groupings), and ontologies (formal logic-based structures) as distinct forms of classification to represent knowledge. Stephen et al. (2023) observe that while domain taxonomies help establish consensus, they lack the formality and scope of ontologies.

As a comparable example, Derave et al. (2024) use both a taxonomy and an ontology for digital platforms to capture both definitions and knowledge. Their taxonomy identifies platform types using both literature reviews and digital platform analysis to identify type gaps from complementary perspectives. The ontology builds on the taxonomy to define a type’s required functional attributes. In AI in media, however, classification remains fragmented, proprietary, and disconnected from product implementation. This project proposes to explore whether a structured but flexible tagging schema can present the basis for a more adaptable, scalable public framework for classifying AI-in-media tools.

Text Classification

Labelling products using automated text classification through Natural Language Processing (NLP) offers greater scalability than manual classification (Li et al., 2022; Allam et al., 2025). Historically, text classification methods are grouped into traditional machine learning (ML) and deep learning (DL) (Li et al., 2022; Aydin, Erdem and Tekerek, 2025). Both use supervised learning with labelled data and can struggle with ambiguous or overlapping class boundaries (Allam et al., 2025). Traditional ML models, like Naïve Bayes (NB) or Support Vector Machines (SVM), rely on hand-engineered features and may miss semantic meaning, but perform well on smaller, structured datasets (Li et al., 2022). By contrast, deep learning models, like Convolutional Neural Networks (CNN) or Recurrent Neural Networks (RNN), automate feature learning and improve semantic representation but require more data and lack transparency.

For more complex classification, pre-trained transformer-based DL models, known as Large Language Models (LLM), like Generative Pre-trained Transformer (GPT), demonstrate higher accuracy, and can perform zero- or few-shot classification with less labelled training data (Allam et al., 2025; Aydin, Erdem and Tekerek, 2025). Attention mechanisms may also increase transparency (Allam et al., 2025). However, LLMs may lack domain-specific knowledge and can hallucinate or misclassify (Abdullahi, Singh and Eickhoff, 2024). Fine-tuning can address this but is resource-intensive and inflexible for fast-changing domains. Alternatively, Retrieval-Augmented Generation (RAG) curates external data to ground LLM outputs, reducing hallucination, improving relevance, and lowering cost (Ramdurai, 2025). This project will explore classification approaches based on their suitability for accurately tagging available AI-for-media product descriptions, while balancing scalability, flexibility, and interpretability.

METHODOLOGY

This hybrid research and development project follows a methodological framework, summarised in Table 1, with Cross Industry Standard Process for Data Mining (CRISP-DM) as its structural framework, excluding deployment (Dawson, 2015; Niakšu, 2015; Saunders, Lewis and Thornhill, 2019).

TABLE 1 | Methodological Summary

PROJECT TYPE (Dawson, 2015)	**PURPOSE** (Dawson, 2015; Saunders et al., 2019)	**PHILOSOPHY** (Saunders et al., 2019)	**REASONING** (Dawson, 2015; Saunders et al., 2019	**PROCESS** (Dawson, 2015; Saunders et al., 2019)	**METHOD** (Saunders et al., 2019)	**STRATEGY** (Saunders et al., 2019	**TIME HORIZON** (Saunders et al., 2019	**DATA** (Saunders et al., 2019)
Research-based	**Exploratory**	**Interpretivism**	**Inductive**	**Evolutionary**	**Qualitative**	**Archival Research**	**Cross-Sectional**	**Secondary**
Development	**Descriptive**	**Pragmatism**	Deductive	Sequential	Quantitative	Case Study	Longitudinal	Primary
Evaluation	**Evaluative**	Positivism	Abductive	Generalised		Ethnography		
Problem-Solving	**Combined**	Critical realism		Circulatory		Action Research		
Industry	Explanatory (Causal)	Postmodernism				Grounded Theory		
						Narrative Inquiry		
						Experiment		
						Survey		

Methodological Framework

This is a **research-based** project with **development** and **evaluation** components (Dawson, 2015; Saunders, Lewis and Thornhill, 2019). It will use an **archival** strategy, sourcing only publicly available **secondary** textual data sources across a **cross-sectional** time horizon from 2024 to 2025.

Because no comprehensive public database of AI in media products exists, **archival research** will be required to identify companies and collect unstructured product descriptions from public industry-verified data sources.

Tagging themes will be validated by literature and product trends to assist classification and assess evaluation. The project's **combined** purpose will **explore** public AI in media products and landscape, **describe** the mapping methodology, and **evaluate** classification (Saunders, Lewis and Thornhill, 2019).

The research will use an **interpretivist** philosophy due to its small in-depth dataset with **qualitative** interpretation, evaluated by limited quantitative model metrics (Saunders, Lewis and Thornhill, 2019). Mixing methods alongside practical tool and technique selection will incorporate elements of **pragmatism.**

Inductive reasoning will identify patterns from specific product examples and generalise them for classification and model performance. The process will be **evolutionary**, iterating tagging and strategies to improve classification accuracy (Dawson, 2015; Saunders, Lewis and Thornhill, 2019).

Data and Analysis

As seen in Figure 1, **CRISP-DM** guides the project across five phases, with deployment out of scope for this project (Niakšu, 2015).

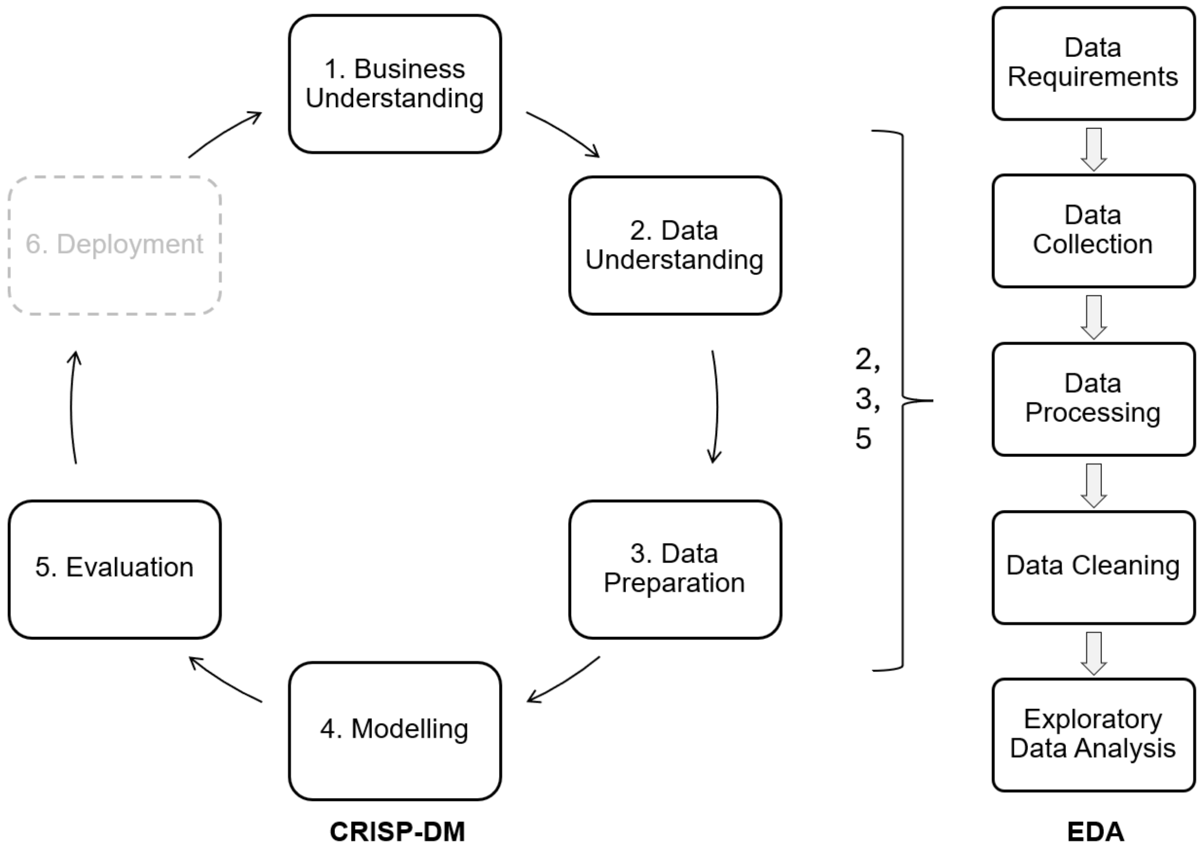


FIGURE 1 | CRISP-DM and EDA

Business understanding, informed by subject expertise and conference feedback, will be validated through academic and industry literature reviews to identify the need for structured understanding of the AI in media landscape.

Data understanding will identify industry-validated sources viable for data collection and assess the best combination of manual and automatic processes for extraction.

Data preparation will clean, structure, format for classification, and store the data. This prepared data will be used alongside structured tagging.

Modelling will use prepared data alongside structured tagging to classify products.

Evaluation will analyse the classified results to determine accuracy and consistency.

Exploratory Data Analysis (**EDA**) will be used iteratively during CRISP-DM data understanding, data preparation, and evaluation to provide insights, identify patterns, and visualise results (Mukhiya and Ahmed, 2020).

Limitations and Challenges

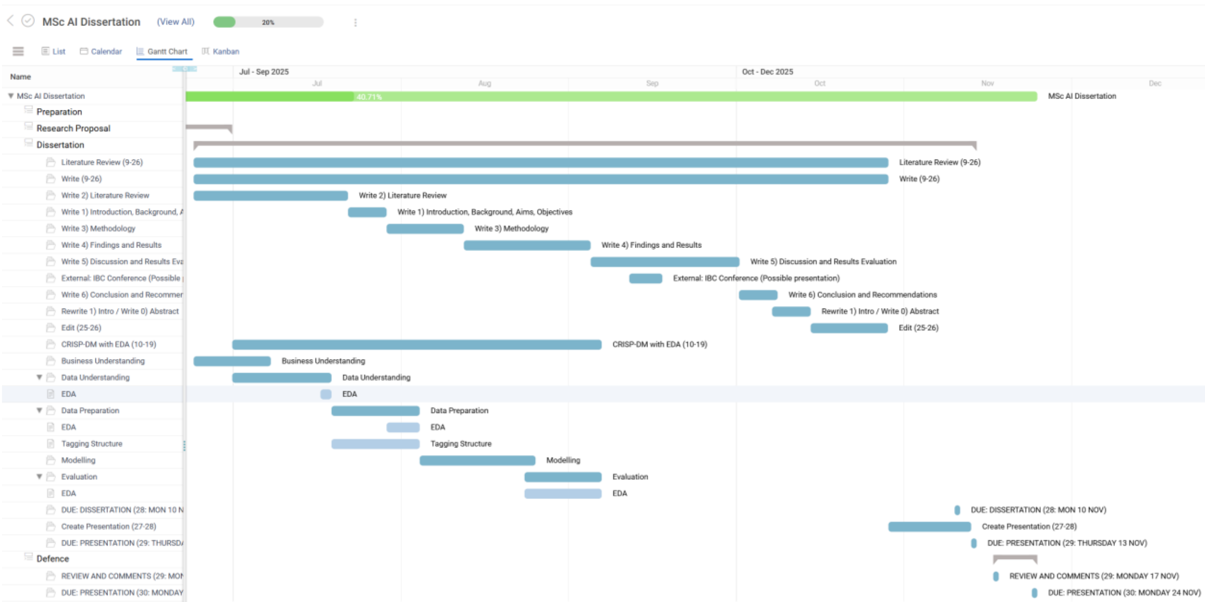
As no structured dataset currently exists, data gathering is limited by the availability and quality of public product descriptions. Limiting the dataset to industry-verified conference sources may result in incomplete coverage of relevant products, and therefore, structured tagging. Additionally, the overall population of AI tools in production, broadcast, and streaming is relatively small, which may limit classification performance. Some products may belong to multiple categories, creating ambiguity during tagging and evaluation.

TIMELINE

Work Packages

WP#	Work Package	Overview	Weeks
WP1	Write Literature Review / Business Understanding	Review academic work on AI in media, tagging, and classification.	9-12
WP2	Write Introduction / Data Understanding	Aim, objectives, research questions. Identify data sources and processes.	12-14
WP3	Write Methodology / Tagging Design / Data Preparation	Methodology, research design, ethics. Design tagging approach. Data collection and preparation.	13-15
WP4	Write Findings / Modelling	Write findings and results as discover. Classify data with model.	15-19
WP5	Evaluation	Evaluate model.	17-19
WP6	Write Discussion / Write Conclusion / Write Abstract	Write discussion and results evaluation. Write conclusion. Rewrite introduction and write abstract.	19-24
WP7	Edit	Edit dissertation.	25-26
WP8	Create Presentation	Prepare presentation.	27-28
WP9	Defence	Review, comments, and present.	29-30

Gantt Chart



Artefacts

This research will develop a dataset of categorised AI tools in media, collected from publicly available sources, and classified using a model. Accompanying this will be a documented tagging approach, iteratively developed using literature-informed schemas and annotation based on use cases. The project will also produce a summary of classification performance and observed patterns on the classified dataset. These artefacts provide inputs for evaluation, and as outputs, a foundation for further research.

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