

# The Economic Impact of the UK’s TDM Approach

## Economic Methodology Note

February 2026

### Introduction

Our goal with this modelling was to explore the extent to which different TDM regulatory regimes would impact the overall potential economic opportunity from AI.

Like any future forecast - particularly one based around as fast-moving technology as AI - there are significant uncertainties including:

- **How AI technology will develop in the next decade.** Our scenarios assume that AI and LLMs will continue to be based on a similar paradigm to today’s transformer models, and that fine tuning will continue to play an important role to develop improved performance for particular use cases.
- **Actual economic impact will depend on the pace of worker and business adoption, and supporting investment to address other infrastructure or skills bottlenecks.** In our core model, we don’t try to model the impact of these factors separately.
- **The day to day impact will depend on how any new regulation is interpreted by businesses.** Based on desk research, we have created stylised scenarios to try and take account of this.

Despite these uncertainties, we believe our modelling gives a reasonable central case for the relative impact of different scenarios for TDM regulation - and the extent to which other factors scale up or down the overall impact of AI would largely proportionally impact the effect of this regulation.

Scenario Definition	
Scenario	Description
<b>Scenario1:</b> A TDM exemption for commercial use (no rights reservation)	<p>This model would allow TDM for all purposes, including commercial use, without requiring permission from rights holders.</p> <p>No reservation mechanism would apply. Once content is made publicly available, it would be freely mineable.</p> <p>In this scenario, we assume that AI reaches its full potential in the UK with no restrictions.</p>

<p><b>Scenario 2:</b> A TDM exemption with a technical opt-out</p>	<p>In this scenario, TDM would be permitted by default, including for commercial use, unless a rights holder has clearly and accessibly opt-ed out.</p> <p>Opt-outs could be communicated through standardised technical measures such as metadata tags or website signals.</p> <p>In this scenario, we assume very minor impacts on use cases requiring fine tuning on internal data and minor restrictions on TDM use cases requiring external data.</p>
<p><b>Scenario 3:</b> A TDM exemption with an opt-out and transparency requirements</p>	<p>TDM would be permitted by default, including for commercial use. Rights holders would have the ability to reserve their rights through a mechanism with legal backing.</p> <p>Additionally new obligations would be required for developers to publish information about how AI models are trained, including but not limited to the use of TDM. These could include summaries of training data sources, explanations of how opt-outs are respected, or information about downstream outputs.</p> <p>In this scenario, we assume minor delays to the deployment and adoption of generic AI tools in the UK, minor impacts on use cases that require fine tuning on internal data and moderate restrictions on TDM use cases requiring external data.</p>
<p><b>Scenario 4:</b> An opt-in model requiring licences for all copyrighted content</p>	<p>Under this model, TDM would only be lawful where rights holders have given explicit permission, typically via a licence.</p> <p>This would offer the strongest level of control to rights holders but would significantly raise the barriers to TDM.</p> <p>In this scenario, we assume moderate delays to the deployment and adoption of generic AI tools in the UK, moderate impacts on use cases that require fine tuning and inference on internal data and that only a minority of TDM use cases that require external data for fine tuning or inference would still be commercially viable. We expect that restrictions on the ability of firms to upload external files for AI inference to significantly limit its effectiveness.</p>

## Modelling Approach

- Our main model exploring the economic impact of AI is a task-based model, following the precedent of [Eloundou et al \(2023\)](#), [Microsoft / Public First \(2024\)](#), and [Felten, Raj and Seamans \(2021\)](#).

- We draw on the US O\*NET database, which sets out the task composition of different types of occupation. For each combination of task and occupation, we use an LLM to classify:
  - how likely it is that task can be augmented by today's AI and machine learning technology
  - how important fine tuning or customisation would be to the performance of AI augmentation on that task
  - how important low latency or self-hosted models would be to the performance of AI augmentation on that task
  - how sensitive a task is likely to be data governance, cultural, regulatory or security requirements, making use of an external API less appropriate
  - to what extent the augmentation of the task would make use of externally source data
- We then aggregate up to the occupation level, looking at the proportion of tasks within each occupation that are potentially augmentable in each scenario.
- We convert from US to UK occupation data, using a crosswalk at the 4-digit level, and then aggregate up from there to 2 digit occupation and individual sectors, based upon lower level occupation's share of total wagebill from ONS data. We use a S-curve diffusion model to project baseline future adoption, which then is adapted depending on the relevant scenario.

### Task Classification Framework

A key component of our methodology is classifying tasks into three distinct groups based on their AI implementation requirements. This classification determines how different TDM regulatory regimes would impact the potential for AI automation and inference for each type of task:

Task Group	Description	Type of inference	Example Use Cases
<b>Off-the-Shelf AI</b>	Tasks that can be augmented using generic, pre-trained AI tools without requiring additional fine-tuning or specialized data. These represent the most accessible AI applications.	Reasoning over non-proprietary data or general knowledge.	General knowledge, coding, translation

<b>Internal Data Fine-Tuning</b>	Tasks where AI performance significantly improves through fine-tuning with an organization's proprietary or internal data, but does not require external data sources.	Reasoning over non-proprietary data or a company's existing internal information.	Company-specific document processing, internal knowledge base queries, proprietary workflow automation
<b>External Data Fine-Tuning</b>	Tasks where AI augmentation depends on training or fine-tuning with externally sourced data, making them most sensitive to TDM regulation.	Reasoning over non-proprietary data, a company's internal data or provided external third-party sources.	Market research synthesis, competitive analysis, content aggregation and curation

This three-way classification is central to understanding how TDM regulation impacts AI potential, as each group faces different levels of restriction under various regulatory scenarios.

### Classification Decision Rules

The classification of tasks into the three groups above is based on two key dimensions derived from LLM-based task analysis:

- **Fine-Tuning Score** (0-1 scale): Measures the extent to which AI performance on a task would benefit from fine-tuning or model customization, rather than using generic off-the-shelf models.
- **External Data Dependency** (0-1 scale): Measures the extent to which effective AI augmentation of the task requires access to external data sources (as opposed to purely internal or no specialized data).

The fine-tuning score itself is calculated as a composite of three decomposed dimensions, each equally weighted:

1. **Data Governance Sensitivity:** How sensitive the task is to data governance, regulatory, cultural, or security requirements that might make external API usage less appropriate.
2. **Latency Sensitivity:** How important low-latency or self-hosted model deployment would be for the task.
3. **Model Customization Benefit:** How much fine-tuning or customization would improve AI performance on the task.