# A Review of AI Techniques and Their Application to Stakeholder Engagement

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## Abstract

As impact assessments grow in complexity, the volume and diversity of stakeholder input poses challenges for meaningful engagement. This paper explores the potential of artificial intelligence (AI), particularly natural language processing (NLP) techniques, to support key steps in the stakeholder engagement process. We evaluate nine AI methods and map them against four common engagement tasks using an AI x Engagement Matrix. Each method-task pair is assessed for applicability, real-world precedent, and associated risks. The results highlight that while language modelling is the most versatile, evaluating stakeholder concerns and responses remains too nuanced for full automation. We argue that AI can enhance efficiency and scale but must be applied strategically to preserve the deliberative and inclusive nature of engagement. This paper provides a framework for identifying where AI can add value, and where caution and human judgement remain paramount in environmental decision-making.

## Introduction

Impact assessment (IA) is a critical tool globally recognized for managing potential impacts of development projects by identifying, predicting, and analyzing impacts, as well as recommending preventative actions (Kim et al., 2024). Central to effective IA is meaning public participation, considered essential for mediating conflicts and upholding democratic decision-making processes (Diduck & Sinclair, 2002; J. Sinclair & Diduck, 1995). Public engagement ensures that legitimate public concerns are heard and that all stakeholders can equally influence decisions.

However, public engagement in IA often faces numerous challenges. Key issues highlighted in the literature include inadequate public understanding of IA processes, participation often limited to procedural hearings, and varied interpretations of what constitutes meaningful involvement (Kim et al., 2024; J. Sinclair & Diduck, 1995). Additional barriers include deficiencies in information dissemination, limited resources, procedural shortcomings, and power dynamics that favour technical expertise or proponent perspectives, thus marginalizing broader public involvement (Diduck & Sinclair, 2002; Reed et al., 2018).

Artificial intelligence (AI), especially natural language processing (NLP) and large language models (LLMs), represent a significant technological advancement capable of addressing many of these engagement challenges while also presenting new complexities (Ngai et al., 2025). NLP allows computers to interpret and generate human languages, encompassing

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technologies essential for meaning extraction, machine translation, text summarization, sentiment analysis, and topic modelling (Zhou et al., 2020). These AI-driven capabilities can enhance public engagement by efficiently analyzing large amounts of textual data, offering timely insights into public sentiment and stakeholder preferences, and streamlining decision-making processes (Ngai et al., 2025).

This paper evaluates the potential applications of AI, particularly NLP-based methods, in supporting stakeholder engagement within IA. It reviews nine NLP techniques against four core engagement processes using an AI x Engagement Matrix, examining each method's applicability, real-world use cases, and associated limitations. By identifying the most effective intersections between AI capabilities and engagement needs, the paper contributes valuable insights to ongoing discussions on leveraging digital tools to improve inclusivity and efficiency in environmental decision-making.

**AI Methods Overview**

NLP studies the fundamental technologies for expressing meaning in words, phrases, sentences, and documents, including syntactic and semantic processing, and develops applications such as machine translation and question-answering (Zhou et al., 2020). NLP is vital for many modern systems, including search engines, customer support, business intelligence, and spoken assistants (Zhou et al., 2020).

A major advancement in NLP has been the emergence LLMs (J. Jia et al., 2023; Mars, 2022). These models are trained on vast amounts of text data in an unsupervised manner, allowing them to acquire sophisticated representations of language (Basha et al., 2023; Mars, 2022). They can then be fine-tuned for specific downstream NLP tasks, often requiring less labeled data and reducing training time significantly (Basha et al., 2023; Mars, 2022).

Below is an overview of the NLP methods that were reviewed for this research. They were chosen based on their frequency of use in NLP research, their relevance to text-heavy stakeholder input and capability to process or generate language in applied settings.

- **Text Classification**: Text classification involves sorting text into predefined categories or labels. It has diverse applications including sentiment analysis, email filtering, and social media monitoring (Dogra et al., 2022).
- **Named Entity Recognition (NER)**: NER identifies and categorizes key information (entities) within text, such as names of persons, locations, and organizations, which is crucial for structed information extraction (Haron et al., 2019).

- **Machine Translation (MT)**: Machine translation automatically converts text from one language to another, crucial in multilingual environments, enhancing communication and accessibility (Ali, 2021).
- **Text Summarization**: Text summarization provides concise versions of lengthy texts, significantly reducing the workload involved in reading and interpreting extensive documentation, reports, or submissions (Zhang et al., 2025).
- **Question Answering (QA)**: Question answering systems respond to human questions in natural language by retrieving and presenting precise answers from extensive datasets, aiding interactive information dissemination (Basha et al., 2023).
- **Language Modelling**: Language modeling predicts subsequent words or sentences based on context, crucial for text generation tasks and facilitating coherent communication outputs (Khurana et al., 2023).
- **Topic Modelling**: Topic modeling identifies underlying themes or topics within large sets of textual data, assisting in thematic analysis and better understanding stakeholder inputs (Mars, 2022).
- **Sentiment Analysis**: Sentiment analysis detects the emotional tone within text data, categorizing statements as positive, negative, or neutral, thus capturing the sentiments of a wide range of groups on specific issues (Dogra et al., 2022).
- **Coreference Resolution**: Coreference resolution determines references of pronouns and nouns within texts, clarifying meanings and enhancing the coherence and comprehensibility of AI outputs (Basha et al., 2023).

**Engagement Processes**

Public engagement is a cornerstone of EIA processes in Canada, recognized as such by various stakeholders (Diduck & Sinclair, 2002; A. J. Sinclair et al., 2012). In this research, we analyzed four engagement steps that we found to be repetitive across the public engagement process that is informed by the *Impact Assessment Act* (2019) on the federal level in Canada. The four main steps we analyzed are:

- **Identify and categorize stakeholders:** In the space of impact assessment, stakeholders have been defined as those who are affected by or can affect a decision (Reed et al., 2018). Identifying and categorizing stakeholders ensures comprehensive representation of affected groups, thereby promoting equitable participation (Reed et al., 2018).
- **Identify communication channels:** Effective engagement requires diverse and accessible communication channels to inform and interact with various publics (Moore, 2016). In addition to traditional methods of communication, utilizing digital

platforms is becoming increasingly important (Doelle, 2017; Moore, 2016; Ulibarri et al., 2019).

- **Evaluate concerns raised in engagement:** Evaluating concerns that are raised in engagement is essential to capture public sentiment, identify externalities, and ensure legitimate public interests are considered in decision-making (Kim et al., 2024).
- **Evaluate responses to concerns given in engagement:** There are multiple mechanisms for responses where the competent authority is expected to justify their decisions and explicitly explain why certain arguments were or were not considered (Palerm, 2000).

**Methodology: The Matrix Approach**

In defining the methods for this research, our aim was to evaluate how specific AI techniques can support different steps in stakeholder engagement during environmental assessments. We focused on mapping the AI capabilities in the previous section to the processes identified previously in the engagement process. This was done to identify high-potential applications and critical limitations. The way we recognized was the best way to visualize this information was through a 4x9 matrix where rows represented AI techniques and columns were engagement steps.

For each cell, we answered three evaluative questions:

- Applicability: Can this AI method reasonably be applied to this engagement step? (+1 if yes)
- Evidence: Are there real-world examples from any domain where this method has been applied to a similar task? (+1 if yes)
- Risk: Are there known risks or limitations with applying this method to this kind of task? (+0 if yes)

Each cell was scored on an additive scale from 0 to 2. A score of 2 showed that there was applicability and evidence in the literature while a score of 0 showed that there was no applicability nor was there any evidence found in the literature. It was assumed that all cells had a +0 since applying an AI technique to any task carries some risk with it.

We gathered evidence from peer-reviewed NLP and AI literature, and other fields like urban planning, transportation, and engineering where public engagement is conducted on some level. There was also grey literature that was looked at to find evidence and applicability.

However, there are limitations to this method. Firstly, the evaluations made were qualitative and assigned a number based on what was found in the literature. Risk wasn’t determined through empirical testing but were rather identified conceptually. The matrix is also exploratory; it's aim is to provoke insight rather than predict performance. This matrix is made for practitioners to understand what AI methods could work for specific engagement processes, but practical implementation will include a more nuanced contextual analysis and deeper validation.

### Results: The AI x Engagement Matrix

| | Identify + Categorize Stakeholders | Communication Channels Used | Concerns Raised | Responses to Concerns |
|---|---|---|---|---|
| Text Classification | 2 | 1 | 0 | 0 |
| Named Entity Recognition | 2 | 0 | 0 | 0 |
| Machine Translation | 0 | 0 | 0 | 0 |
| Text Summarization | 0 | 0 | 2 | 2 |
| Question Answering | 0 | 0 | 1 | 2 |
| Sentiment Analysis | 0 | 0 | 2 | 1 |
| Coreference Resolution | 1 | 1 | 0 | 0 |
| Language Modelling | 1 | 2 | 1 | 2 |
| Topic Modelling | 0 | 1 | 2 | 1 |

*Figure 1 The AI x Engagement Matrix*

From this matrix, we see that language modelling has emerged as the most adaptable AI method. It scored a 1 or 2 across all engagement processes, being the only method to do so. The reason for this is that it is a new and versatile method that is effective in tasks involving text generation, pattern recognition, and summarization.

There are also other methods worth mentioning that scored quite highly on this matrix. Text classification is a good task for identifying and categorizing stakeholders as well as identifying relevant communication channels. Question answering, on the other hand, can be used to find concerns raised and how they were responded to. These two engagement steps also have less applicability and real-world examples, meaning that they require human and ethical judgement as well as contextual basis to make decisions on stakeholders and using communication channels.

Additionally, concerns raised and responses to concerns were the most complex engagement steps evaluated. They are the two steps that could involve multiple AI methods in their analysis – from text summarization to topic modelling. We did not find applicability or evidence of coreference resolution being used in these steps. With the use of multiple AI methods and the risks associated with them, these steps are automatable but require higher human insight in the way they are handled.

Lastly, we see that machine translation has a score of 0 for every engagement step. We would like to note that, while we focused on a monolingual engagement process, this is not the case everywhere. In a monolingual context, machine translation does not have much of a use case. However, in a multilingual context, machine translation is an extremely useful AI method and one of the oldest methods in the field (Kenny, 2022).

### Risks and Limitations

The integration of AI methods, including LLMs, into public engagement processes introduces several notable risks and limitations (Ngai et al., 2025). A primary concern involves data privacy, as AI systems often process sensitive personal information, heightening the risk of unauthorized access or data breaches, which can lead to legal complications and erosion of public trust (Ngai et al., 2025; Yang et al., 2024).

Additionally, NLP algorithms trained on existing datasets may inadvertently reinforce existing biases, potentially leading to discriminatory outcomes and undermining fairness in decision-making processes (Castillo-Campos et al., 2025; Ngai et al., 2025). The inherent opacity of LLMs, often described as "black boxes", further exacerbates these concerns, as their decision-making mechanisms are difficult to interpret, challenging accountability and transparency in public engagements (J. Jia et al., 2023; Ngai et al., 2025).

Furthermore, AI systems may struggle with nuanced language elements such as sarcasm, regional idioms, or culturally specific expressions, potentially misinterpreting public sentiments and skewing results (Castillo-Campos et al., 2025; Ngai et al., 2025). "Hallucinations", where LLMs generate fluent yet incorrect or nonsensical outputs, also pose significant risks, potentially misleading stakeholders and decision-makers (Yang et al., 2024).

Lastly, LLMs have inherent limitations related to their context length, hindering their ability to fully process and generate comprehensive responses from extensive texts, thus risking information loss (Acheampong et al., 2021; Z. Jia & Lee, 2025; Yang et al., 2024).

While AI holds substantial promise for improving public engagement and IA decision-making, these risks must be carefully managed and proactively mitigated to ensure responsible and effective implementation.

### Conclusion

This paper has explored how various AI techniques can support key steps in stakeholder engagement within IA processes. By developing and applying a matrix, we mapped nine AI methods against four core engagement tasks, evaluating their applicability, real-world precedent, and potential risks. The analysis reveals that language modelling stands out as the most versatile technique, with significant potential across multiple stages of engagement. The results also highlight that evaluating stakeholder concerns and responses remains a complex area where multiple AI methods can be used, leading to greater risk, and underscoring the necessity of human judgement.

Our findings suggest that while AI can enhance efficiency, scale, and consistency in engagement processes, its integration must be strategic and context sensitive. Rather than seeking to replace human roles, AI tools should be deployed to support inclusive, transparent, and responsive engagement that align with best-practice principles in IA decision-making. Future research in this project will focus on creating a proof-of-concept to analyze how well AI can track stakeholder concerns and their coverage in IA documents.

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