Technological Forecasting & Social Change 225 (2026) 124553

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Waste management–related trust, acceptance, and reputation: A multidisciplinary big data analysis across knowledge domains

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ARTICLE INFO

Keywords:
Trust
Acceptance
Reputation
Perception
Large-scale media analysis
Opinion mining
Classification analysis
Artificial intelligence (AI)

ABSTRACT

Addressing global waste management challenges requires understanding not only the technical capabilities of products and technologies but also the factors shaping their development and deployment across the waste hierarchy. Deployment outcomes are strongly influenced by acceptance, reputation, and trust, distinct yet interrelated constructs whose dynamics remain insufficiently understood. Deepening this understanding can enhance stakeholder engagement and improve decision-making in waste management. This study examines waste-to-energy incineration as a representative case to investigate these dynamics across global, regional, and local levels. A multidisciplinary, data-driven approach is applied, combining artificial intelligence, big data analytics, opinion mining, Correspondence Analysis on Generalized Aggregated Lexical Tables, and content classification to assess acceptance, trust, and reputation in multiple knowledge domains. The analysis clarifies these constructs as interwoven but individually influential factors shaping technology deployment and explores their interplay with public perception. A novel method is also introduced for generating indicative reputation scores derived from sentiment analysis. The findings show that AI-enhanced analytical tools, when integrated with established methods, yield valuable insights into stakeholder sentiment and public discourse. These insights can inform more targeted stakeholder engagement and strategic communication in waste management planning. Overall, the study demonstrates the potential of emerging analytical tools to produce timely, structured indicators of trust, acceptance, and reputation, key dimensions for navigating the socio-political challenges of technology deployment in the waste sector.

1. Introduction

Global municipal solid waste generation reached 2.1 billion tons in 2023 and is projected to rise to 3.8 billion tons by 2050, nearly ten times the mass of Mount Everest (UNEP, 2024). Earlier projections (Bhada-Tata and Hoornweg, 2012; Chen et al., 2020) warned of this trend, from 635 Mt. in 1965 to nearly 3.5 billion tons by mid-century. These escalating figures highlight both the scale of the challenge and the urgency of addressing infrastructural, regulatory, and, above all, societal barriers. Addressing this crisis requires more than technical solutions; it demands approaches that integrate public perception, legitimacy, institutional trust, and perceived fairness in technology deployment.

Prior research has begun to examine these aspects. Studies emphasize that community-targeted corporate social responsibility (CSR) and public trust are vital for the societal acceptance of contested infrastructures, such as waste-to-energy (WtE) incineration. For example, Aga and Beyene (2025) show that public trust mediates the relationship between environmental responsibility and acceptance, reinforcing trust as a transmission mechanism for infrastructure legitimacy. Similar findings in other sectors indicate that externally driven, community-oriented CSR enhances stakeholder trust and contributes to organizational legitimacy (Shahid, 2025). Trust also amplifies the perceived benefits of technologies and shapes behavioral intentions in both digital and infrastructure contexts (Adaryani et al., 2024).

This issue is particularly salient in the context of WtE incineration, which, despite its technical merits, faces persistent public resistance due

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https://doi.org/10.1016/j.techfore.2026.124553
Received 24 March 2024; Received in revised form 10 November 2025; Accepted 15 January 2026
Available online 23 January 2026

to its controversial image and historical mistrust (Tsui and Wong, 2019). In addition to socio-political resistance, WtE projects face commercialization barriers, such as regulatory complexity, market uncertainty, financing constraints, and technical limitations (Yong et al., 2023). However, prior research shows that these barriers are frequently amplified by public perception, including how policies are framed, interpreted, and received (Żuk, 2023). Environmental concerns and regulatory environments further shape the introduction of WtE and related technologies (Shakeel et al., 2017).

Traditional frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), though widely applied, have been criticized for insufficiently capturing the contextual, cultural, and psychological dimensions of value-sensitive technology acceptance (Blut et al., 2022). Yet, little is known about how constructs such as trust, fairness, and emotional narratives manifest in public discourse around contested infrastructures. Stakeholder-centric approaches highlight the relational nature of acceptance, incorporating concerns such as environmental justice, post-adoption trust, and value alignment. For instance, Jaiswal et al. (2025) apply stakeholder-informed machine learning in ESG contexts, revealing how multidimensional sentiments shape acceptance under uncertainty.

The role of media and sentiment has also become pivotal. ESG-related coverage has been shown to stimulate corporate energy innovation by enhancing reputation (Tan et al., 2025), while media framing strongly influences public discourse around energy transitions (Kim et al., 2024). Moreover, social media sentiment mediates the relationship between environmental performance and public reputation (Islam et al., 2025). Together, these studies highlight the growing importance of digital trust markers (Krishna and Puram, 2025) and emotion-laden cues in shaping socio-technical acceptance.

Despite these insights, important methodological gaps remain. Most acceptance studies rely on survey-based approaches, overlooking the potential of digitally enabled, multi-method designs. This raises our guiding question: How can large-scale AI-assisted discourse analysis advance the understanding of technology acceptance, trust, and reputation in the context of WtE incineration?

To address this gap, we employ a triangulated methodology combining large-scale opinion mining, AI-assisted analysis using ChatGPT, Correspondence Analysis on Generalized Aggregated Lexical Tables (CA-GALT), and manual content classification. Together, these complementary methods enable a nuanced exploration of the multi-layered dynamics underpinning sentiment, trust, and reputation. Recent advances in explainable AI and sentiment interpretation (Wang et al., 2025; Xu et al., 2024) further highlight the analytical value of these tools for examining public perceptions of technology. By integrating computational discourse methods with established acceptance theories, this study bridges the gap between behavioral models and real-world stakeholder sentiment, offering a novel lens for analyzing legitimacy and trust in sustainability-oriented technologies.

Our findings indicate that acceptance, trust, and reputation toward WtE incineration are context-dependent, varying by region, institutional trust, and socio-political framing. Trust emerges as the strongest mediator between perception and acceptance, while media sentiment serves as a reliable proxy for public discourse trends. These results emphasize the pivotal role of transparency, fairness, and technological performance in shaping stakeholder confidence and legitimacy.

This study makes three key contributions: (1) Theoretically, it extends established models (TAM, UTAUT) by integrating trust, fairness, and emotional resistance as central constructs, demonstrating how they manifest in large-scale, real-world public discourse. (2) Methodologically, it introduces a hybrid AI–discourse triangulation that captures acceptance dynamics at scale, addressing the limitations of survey-dominated approaches. (3) Practically, it provides municipalities, operators, and regulators with a structured framework to anticipate stakeholder resistance, strengthen trust, and enhance the social license to operate in contested infrastructure projects such as WtE. These contributions are elaborated in Section 5 and reinforced in the Conclusion.

2. Literature review

Global household waste is increasing rapidly (Bhada-Tata and Hoornweg, 2012). Although volumes vary by region, only about 30% is currently recycled (Kountouris and Remoundou, 2023). Recycling rates for specific materials remain low: 10% for tires, 19.5% for plastics, and 21% for glass (Ferdous et al., 2021). Plastic is especially problematic due to its persistence and ocean accumulation (Chow et al., 2017). A comprehensive life-cycle approach, from design and raw materials to consumption, recycling, and disposal, remains lacking (Singh et al., 2014). In the EU waste hierarchy, incineration and energy recovery rank below reduction, reuse, and recycling (Zhang et al., 2022). Nevertheless, improving these technologies remains essential. WtE converts waste into fuel for electricity, heating, and cooling (Kalogirou, 2017). While WtE reduces waste volume and enables energy recovery, environmental concerns remain, particularly regarding emissions of dioxins, furans, and greenhouse gases (Margallo et al., 2012; Buonanno et al., 2010; Buonanno and Morawska, 2015).

2.1. Product and technology acceptance, trust & reputation

Product and technology acceptance, trust, and reputation are closely interlinked concepts that significantly influence how innovations are perceived and adopted (Table 1).

Key factors influencing acceptance include safety, perceived risks and benefits, trust, distance, cost, knowledge, and reliability (Liu et al., 2019; Mousavi et al., 2022). Trust is fostered when technologies demonstrate safe design and operation, minimizing harm (Greenberg, 2014). WtE incinerators, in particular, evoke skepticism due to environmental and health concerns (Caferra et al., 2023). Trust grows when technologies meet environmental standards and reduce waste and emissions (Chen et al., 2017). Transparency in design, operation, and

Table 1
Interlinkages among product and technology acceptance, trust, and reputation.

Product Acceptance and Trust	Product Reputation and Trust	Product Reputation and Product Acceptance
Trust plays a pivotal role in product acceptance. When there is confidence in a product, brand, or organization, stakeholders are more inclined to adopt it, as trust helps to align expectations and diminishes perceived risk. (Ta and Prybutok, 2018)	A strong reputation fosters trust. Brands known for quality, ethics, and customer satisfaction are more trusted. Reputation thus serves as a foundation for building trust. (Berens and van Riel, 2004).	A positive reputation increases acceptance. Stakeholders are more willing to adopt products associated with reputable brands. (Yao et al., 2009).

Technology Acceptance and Trust	Technology Reputation and Trust	Technology Reputation and Technology Acceptance
Trust is central to technology acceptance. Reliable, ethical, and secure technologies reduce perceived risk, increasing use and integration (Pavlou, 2003; Norfolk and O'Regan, 2021).	Reputation affects the trust placed in technology. A positive reputation enhances perceived reliability and safety, while negative events can erode trust. (Yang and Wibowo, 2022).	Technologies with strong reputations for usability, effectiveness, and benefits are more likely to gain acceptance. Reputation can also influence societal attitudes. (Ejdys, 2018).

Finding: Acceptance, trust, and reputation are mutually reinforcing but fragile. Negative experiences can damage trust or reputation, limiting acceptance.

monitoring further builds trust (Feng et al., 2020), enabling the public to better understand risks (Zhang, 2014). Engagement with local stakeholders also enhances social acceptability and trust (Wüstenhagen et al., 2007).

Public acceptance can shape energy technology deployment through its influence on policy, legal frameworks, and decision-making (Nuortimo and Harkonen, 2018). Resistance can delay or derail deployment (Xavier et al., 2017). Prior studies have applied machine learning and opinion mining to study public acceptance of nuclear (Nuortimo and Harkonen, 2019a; Ong et al., 2022), coal (Nuortimo and Harkonen, 2019b), carbon capture and storage (CCS) (Aviso et al., 2019; Nuortimo et al., 2018a; Yao et al., 2023), biomass (Nuortimo et al., 2017), solar (Kim et al., 2021; Nuortimo et al., 2018c), and wind energy (Fischhendler et al., 2021; Nezhad et al., 2022; Nuortimo et al., 2018b). Advances in multi-stakeholder sentiment analysis have improved diagnostic depth (Jaiswal et al., 2025), while traditional manual methods remain common but error-prone.

Trust remains a foundational factor in WtE adoption (Bui and Tseng, 2022). People must trust that the technology will function as intended with minimal environmental or health risks. This trust is tied to both technological performance and operators' reputation (He et al., 2023). Transparency, stakeholder participation, and community initiatives can foster this trust and lead to broader acceptance (Liu et al., 2018). Conversely, poor reputation and low trust can hinder uptake (Kowalska-Pyzalska, 2018).

A positive product reputation often signals reliability, quality, and alignment with customer expectations. However, avoiding dissatisfaction may depend on which features matter most (Jokela, 2004). For WtE incinerators, reputation often hinges on regulatory compliance and demonstrated environmental performance (Seltenrich, 2016; Makarichi et al., 2018). Local community engagement can further reputation (Pascaris et al., 2021).

Reputation assessment involves gauging stakeholder perceptions, including users, competitors, experts, and the general public, using defined metrics and goals (El Marrakchi et al., 2016). Key indicators include customer satisfaction (Zhang et al., 2003), user reviews (Abrate and Viglia, 2019), media coverage (Watanabe et al., 2020), social media presence (Ram and Zhang, 2023), risk perception (Biswas et al., 2006), and word-of-mouth (WOM) (Lee and Choeh, 2020). Data can be gathered via surveys, online reviews, opinion mining (Piao et al., 2019), media monitoring, and sentiment analysis (Liu, 2022; Nuortimo and Harkonen, 2022). Perceived reputation affects deployment prospects (Hirmer and Cruickshank, 2014), but reputation is built gradually through quality, experience, and communication.

Perception is tightly interwoven with acceptance, trust, and reputation. How technologies are perceived influences public and stakeholder responses, which in turn shape trust and reputation. This is particularly critical for WtE incinerators, which often face scrutiny and local resistance. Moreover, perception influences broader systems, including policy, regulation, and deployment speed. A detailed overview of these interconnections is presented in Appendix A (Table A.1).

Finding: Perception is closely intertwined with acceptance, trust, and reputation, and can affect energy technology policies, legal and regulatory frameworks, and market deployment, and hence influence the adoption of WtE incinerators and other technologies in waste management.

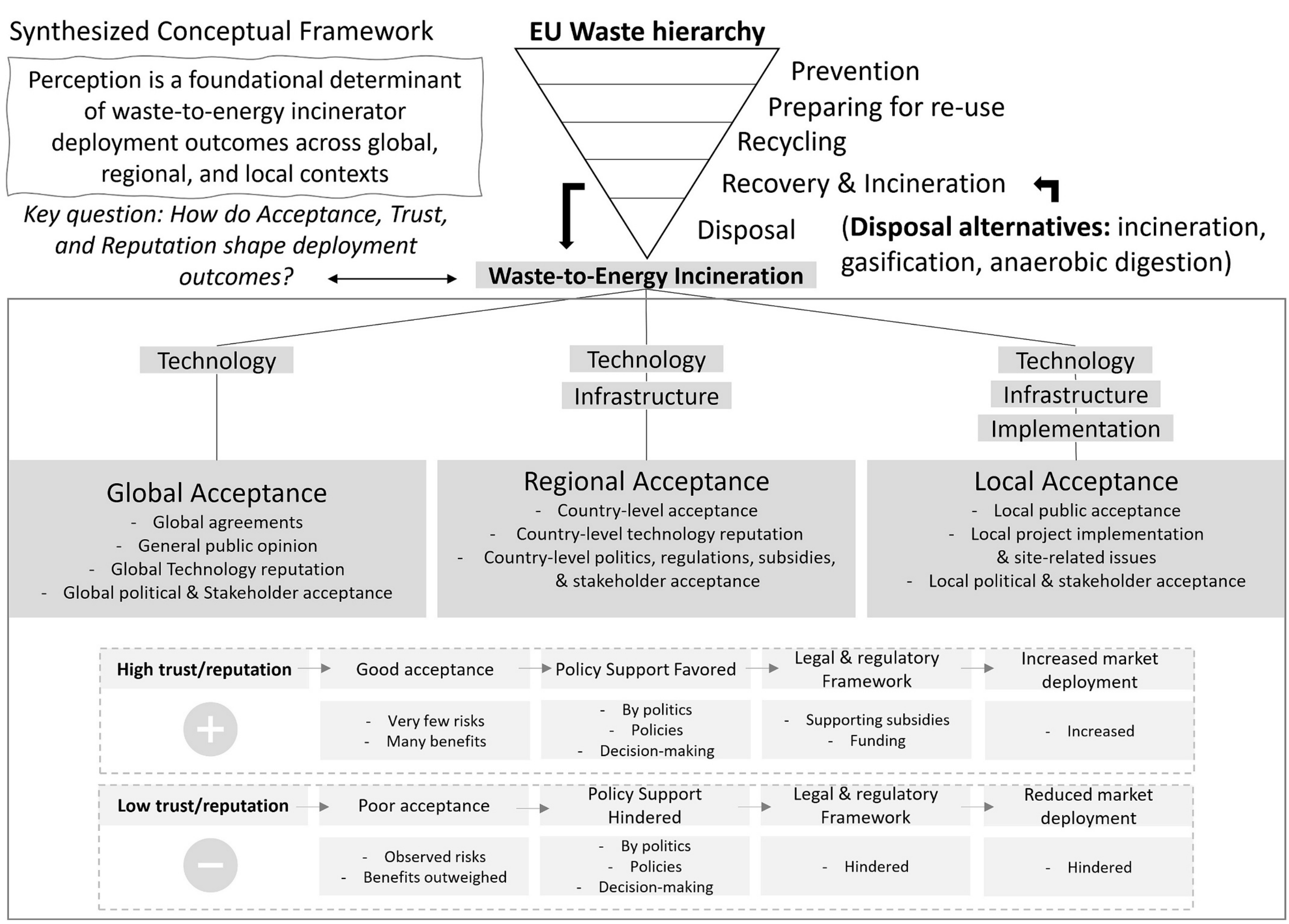

Fig. 1. Synthesized EU waste hierarchy-based framework linking acceptance, trust, and reputation to WtE market deployment.

Fig. 1 presents a synthesized EU waste hierarchy-based framework to study how acceptance, trust, and reputation influence WtE incineration deployment. While disposal remains the least preferred option (e.g., Zhang et al., 2022), the negative perception of WtE impedes its broader adoption. Measuring the soft factors may help identify deployment barriers and improve waste management outcomes.

2.2. Theoretical underpinnings

Understanding the dynamics of acceptance, trust, and reputation in the context of WtE incineration requires grounding in established theories from Information Systems (IS) and Organizational Behavior (OB). IS models, such as TAM (Davis, 1989), UTAUT (Venkatesh et al., 2016), and Trust in Technology frameworks (Li et al., 2008) are highly relevant, as WtE incineration represents a technical innovation dependent on public and stakeholder acceptance. These models have been applied beyond the IT domain to explain how individuals and groups adopt new technologies, including environmental technologies (Koo and Chung, 2014) and smart infrastructure (Jena, 2022).

OB contributes complementary theories on trust (Dirks and de Jong, 2022), risk perception (Weber et al., 1992), reputation management (Doering et al., 2021), and stakeholder engagement (Watson et al., 2018). These frameworks are especially useful in analyzing institutional trust, organizational reputation, and community–industry relations. Accordingly, this study integrates TAM, UTAUT, and trust-based frameworks as a conceptual foundation for empirical analysis and interpretation.

Critically, public perception of WtE incineration is shaped not only by general attitudes toward innovation but also by context-specific concerns, such as environmental sustainability, health risks, and distributive fairness. Theories of perceived risk (Weber et al., 1992) and procedural justice (Walker, 2012) are particularly applicable, as they address how individuals evaluate fairness in risk–benefit distribution.

Communities may judge technologies like WtE not only on technical performance but also on how equitably risks and benefits are perceived to be distributed. High institutional or community trust can reduce perceived risk, whereas low trust, particularly in contexts with prior environmental controversies, can amplify opposition. This perspective aligns with recent findings (Tan et al., 2025), which show that public trust in environmental technologies is influenced by procedural transparency and distributive fairness, especially in cases involving visible trade-offs. Similarly, research drawing from resource-based and legitimacy theories suggests that corporate reputation and public sentiment function as strategic assets, shaping both stakeholder responses and financial outcomes (Islam et al., 2025).

Table 2 summarizes the core theoretical constructs and their measurement proxies used in the framework.

2.2.1. Technology acceptance

The TAM (Davis, 1989) and its extensions (Venkatesh and Davis, 2000; Venkatesh et al., 2003; Türker et al., 2022) provide a foundational framework for understanding how individuals and communities adopt technologies. According to TAM, two core factors influence acceptance: *Perceived Usefulness (PU)*, the belief that a technology enhances performance or delivers value (e.g., WtE reducing landfill volume and generating energy); and *Perceived Ease of Use (PEOU)*, the belief that using the technology requires minimal effort (Venkatesh and Bala, 2008), such as smooth integration of WtE into existing waste infrastructure.

Table 2
Core constructs and measurement proxies used in the theoretical framework.

Concept	Key Attributes	Measurement Proxy
Trust	Competence, Integrity, Benevolence	Sentiment, community discourse
Reputation	Accumulated public evaluation over time	Media coverage, eWOM, sentiment polarity
Perception	Stakeholder viewpoints (contextual, evolving)	Sentiment, opinion mining, public framing
Acceptance	Behavioral intention to support/ use technology	Sentiment, adoption discourse

The UTAUT extends TAM by introducing: *Performance Expectancy*, *Effort Expectancy* (Rahi et al., 2019), *Social Influence* (Khechine et al., 2020), and *Facilitating Conditions* (Twum et al., 2022). Recent meta-analyses, however, have raised concerns about UTAUT's generalizability across diverse domains, particularly in complex contexts like environmental infrastructure (Blut et al., 2022), where contextual sensitivity is crucial. Illustrative applications in the WtE context include: *Performance Expectancy (PE)*: A municipal official expecting WtE to improve waste efficiency and energy generation; *Effort Expectancy (EE)*: Residents perceiving minimal behavioral changes required (e.g., separating waste); *Social Influence (SI)*: Public support based on social endorsement of WtE as a responsible solution; and *Facilitating Conditions (FC)*: Supportive infrastructure (modern trucks, public campaigns) that ease participation.

Importantly, Adaryani et al. (2024) show that *information literacy* conditions how stakeholders perceive infrastructural readiness, highlighting that enabling environments must include both physical assets and informational scaffolding.

In this study, media-based sentiment (Liu, 2022) and opinion mining (Pang and Lee, 2008; Nuortimo et al., 2017) are used as proxies for Perceived Usefulness (Venkatesh and Bala, 2008) and Performance Expectancy (Rahi et al., 2019), particularly regarding energy generation, emission control, and environmental benefits. Social Influence (Khechine et al., 2020) is operationalized via discourse themes (e.g., community resistance or advocacy), while Facilitating Conditions are inferred from references to policy, infrastructure, and informational support.

2.2.2. Trust in technology

Trust serves as a central mediating factor between perception and acceptance. Building on McKnight et al. (2002) and Siegrist and Cvetkovich (2000), trust in technology comprises three dimensions: *Competence Trust* (belief in the technology's ability to perform as expected; Low et al., 2023); *Benevolence Trust* (belief that developers or operators act in the public's best interest; Ibrahim et al., 2023); and *Integrity Trust* (belief in adherence to ethical and safety standards; McKnight et al., 2011).

Trust is shaped by perception (Jiang et al., 2022) and influences both acceptance and reputation (Bui and Tseng, 2022; Dirks and de Jong, 2022). Evidence from large-scale infrastructure projects shows that community-targeted social responsibility and trust in implementing agents are pivotal to public acceptance of contested technologies. For instance, Aga and Beyene (2025) found that trust fully mediated the relationship between environmental responsibility and acceptance, and partially mediated the link between community responsibility and acceptance, highlighting trust as a transmission mechanism for public support in megaprojects. Negative safety perception can diminish competence trust, thereby reducing acceptance. In contrast, transparent community engagement can enhance integrity trust and strengthen reputation.

2.2.3. Reputation and perception

Although reputation is not explicitly part of TAM or UTAUT, it aligns with their feedback-loop logic, wherein experiences, reviews, and external perceptions shape social norms and future behavioral intentions (Vorm and Combs, 2022). In this context, reputation can function both as an input to trust and an outcome of acceptance (Berens and van Riel, 2004; Chun, 2005; Makarichi et al., 2018).

Electronic word-of-mouth (eWOM), including social media discourse and user-generated reviews, plays a growing role in shaping technological reputation, particularly in digital and energy domains (Gelashvili et al., 2024). Sentiment analysis (Liu, 2022) of media and social content acts as a proxy for collective perception (Jiang et al., 2022) and reputation status, especially where direct stakeholder surveys are lacking.

Recent findings highlight the power of media framing in influencing emotional reactions and shaping discourse quality around energy transitions (Kim et al., 2024). The reputation score proposed later in this study reflects this logic, enabling benchmarking across geographic and contextual boundaries.

2.2.4. Integrative framework

The integrated framework presented in Fig. 2 synthesizes elements from TAM, UTAUT, and trust theory, outlining a multi-stage pathway from perception through trust, reputation, and ultimately to acceptance.

This conceptual model underpins the study's empirical strategy, which combines sentiment analysis, AI-assisted interpretation, and media classification to evaluate acceptance, trust, and reputation across global, regional, and local levels (see Section 3).

3. Methods and their application

This study adopts a triangulated methodology to gain a holistic yet reliable view of WtE incinerator-related acceptance, trust, and reputation. By integrating complementary methods across different knowledge domains, the approach enhances interpretative depth and offsets limitations inherent in single-method designs, such as algorithmic opacity in sentiment tools or overgeneralization in AI models.

At the core, the research utilizes big data sourced through opinion mining, where sentiment, defined as the emotional tone or evaluative attitude toward WtE, is extracted and analyzed (Liu, 2022). Sentiment can be positive, negative, or neutral, and reflects public perception in context (Pang and Lee, 2008). However, sentiment-based measures of acceptance are inherently indicative and prone to error. Recent studies confirm the value of electronic word-of-mouth (eWOM) and perceived privacy in shaping trust and satisfaction (Gelashvili et al., 2024). This highlights the relevance of integrating trust constructs into socio-technical analysis (Earle, 2010).

Trust is critical for technology adoption and reputation (Donnison et al., 2023; Bui and Tseng, 2022), especially in high-stakes domains like environmental infrastructure (Buaprommee and Polyorat, 2016). Krishna and Puram (2025) demonstrate how text-mined sentiment dimensions, such as information quality and privacy, predict stakeholder satisfaction. To strengthen methodological rigor, ChatGPT (OpenAI, 2023), is applied to support the contextual interpretation of sentiment data. Additional tools include CA-GALT (Bécue-Bertaut and Pagès, 2015; Kostov et al., 2015) for latent pattern detection and manual content classification (Rauchfleisch et al., 2023) to extract product-specific insights.

These methods were chosen for their complementary strengths:

- Opinion mining (M-Brain) provides scalable, multilingual sentiment analysis;
- ChatGPT supports nuanced interpretation across global, regional, and local scales;
- CA-GALT enables country-level discourse clustering;
- Manual classification adds interpretive validation.

Together, they offer both breadth (via automated tools) and depth (via human triangulation), enabling a multi-scalar understanding of stakeholder dynamics, particularly given that technology-related perceptions can strongly influence adoption and progress (Choi et al., 2008). Table 3 summarizes the methodological design:

To ensure conceptual alignment between theory and empirical analysis, we mapped the four core constructs, trust, reputation, perception, and acceptance, to operational definitions and corresponding analytical techniques. These constructs are examined using a triangulated approach that combines sentiment analysis, CA-GALT, ChatGPT-assisted interpretation, and manual classification. This mapping enhances construct validity and ensures methodological transparency. Appendix B (Table B.1) summarizes this alignment.

To the best of our knowledge, this is the first study applying ChatGPT to analyze WtE incineration acceptance. While opinion mining and CA-GALT are established methods (Pang and Lee, 2008; Kostov et al., 2015), their integration with AI-assisted interpretation and manual coding enhances triangulation and validity.

Fig. 3 illustrates the research process and methodology, integrating the AI tool with established research frameworks.

The methodological process follows three sequential phases: (1) big data sentiment extraction via opinion mining and AI tools; (2)

Table 3
Overview of key constructs and their measurement proxies in the context of WtE acceptance.

Method	Focus Area	Measurement level
Opinion Mining (M-Brain)	Sentiment Analysis	Regional
AI (ChatGPT)	Acceptance, Trust, Reputation, Sentiment	Global, Regional, Local
CA-GALT analysis	Country-Level Clustering	Regional
Manual Content Classification	Local Product Reputation	Local

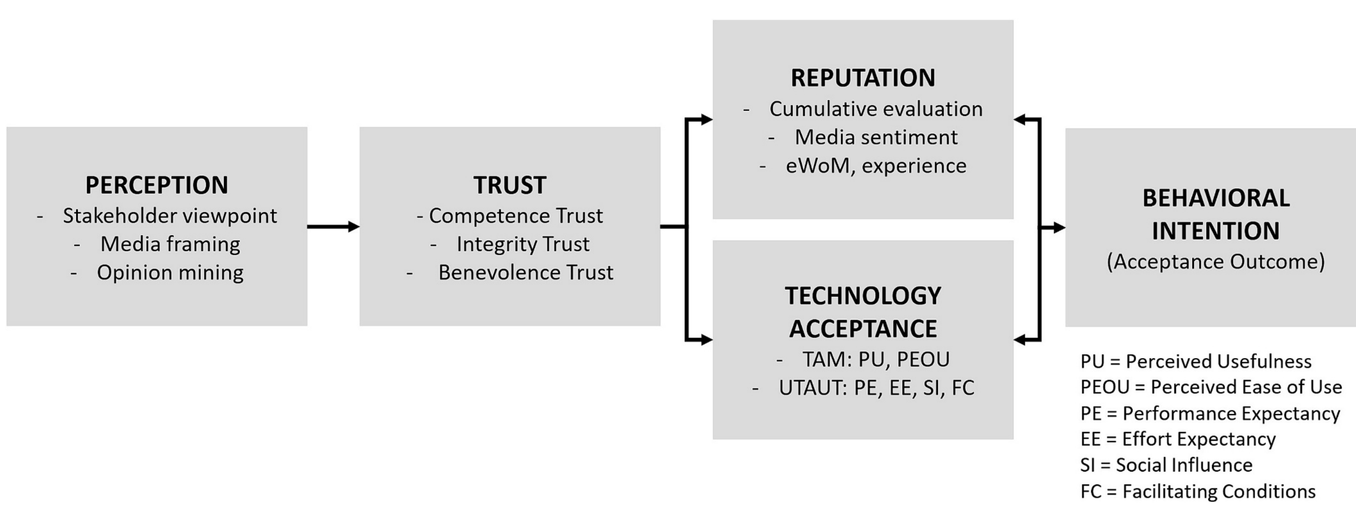

Fig. 2. Integrated theoretical framework for WtE incineration acceptance, trust, and reputation.

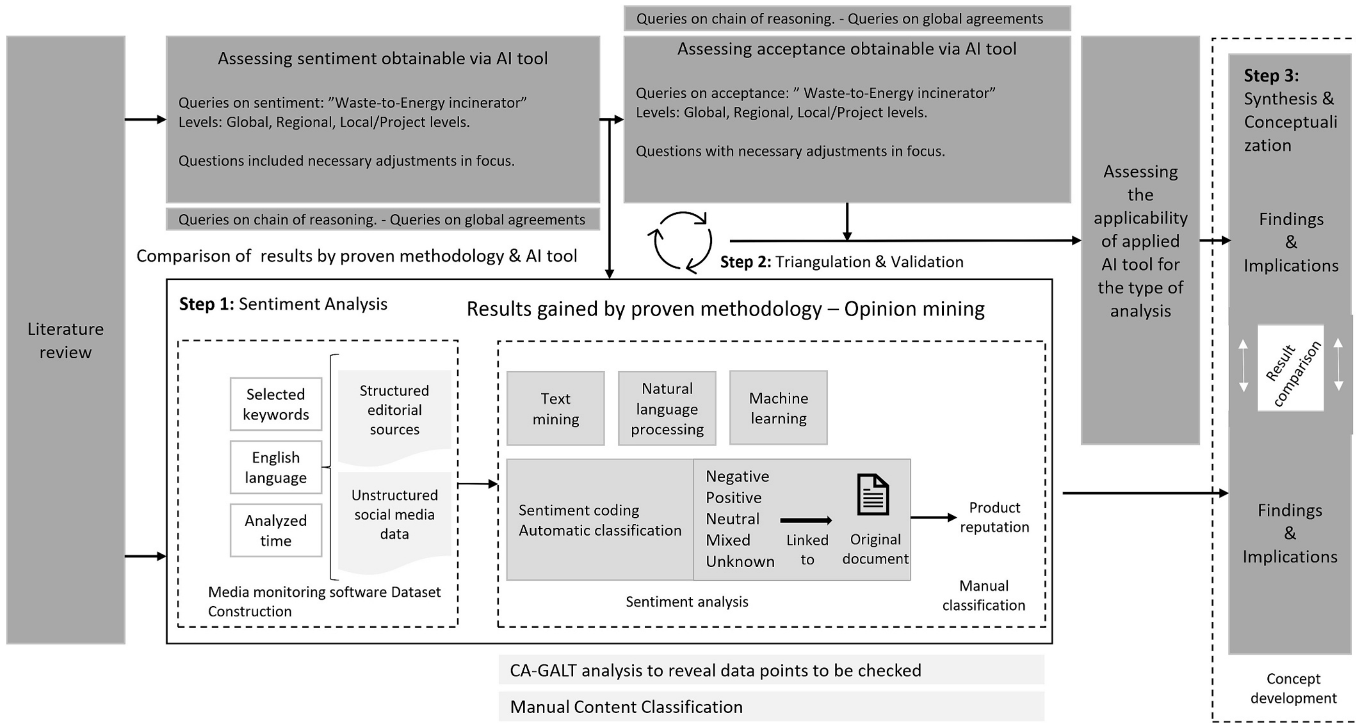

Fig. 3. Research process and methodology.

triangulation and validation through CA-GALT clustering and manual analysis; and (3) comparative synthesis to interpret results and derive implications.

This multi-step approach ensures comprehensive coverage of global, regional, and local acceptance and reputation dynamics, while addressing socio-cultural context through indirect discourse cues.

The following section details each methodological component.

3.1. Opinion mining via media monitoring

Opinion mining (e.g., Pang and Lee, 2008) is used as the core method due to its extensive validation across domains, including energy technologies such as biomass (Nuortimo et al., 2017), CCS (Aviso et al., 2019; Nuortimo et al., 2018a; Yao et al., 2023), coal (Nuortimo and Harkonen, 2019b), nuclear (Nuortimo and Harkonen, 2019a; Ong et al., 2022), solar (Kim et al., 2021; Nuortimo et al., 2018c), and wind (Fischhendler et al., 2021; Nezhad et al., 2022; Nuortimo et al., 2018b). Petz et al. (2014) provide a comprehensive overview of computational opinion mining approaches, further supporting its methodological basis.

This study applies a commercial media monitoring tool (M-Brain, 2015) to analyze editorial and social media sentiment (Liu, 2022). The tool processes over 3 million platforms and 100,000 news sources across 71 languages and 236 regions, allowing large-scale sentiment analysis using machine learning and natural language processing. While manual methods are feasible (Rauchfleisch et al., 2023), they are limited in scale (Nuortimo, 2021).

To ensure consistency, only English-language content was analyzed. Data were filtered using structured queries related to WtE incineration and its acceptance, trust, and reputation. Irrelevant or duplicate entries were removed during preprocessing. Results were segmented by geographic region (Global, Regional, Local) and sentiment polarity (positive, negative, neutral). Extreme sentiment samples were manually validated following Lappeman et al. (2024) and Rauchfleisch et al. (2023) to correct for classification errors and improve interpretability.

The M-Brain tool functions as a black box, where inputs/outputs are accessible, but algorithmic internals are proprietary (Nuortimo, 2021). Although transparency is limited, the system applies consistent logic across texts, enhancing reliability and comparability. With classification accuracy around 80%, often exceeding human agreement, the approach is suitable for scalable, repeatable analysis (Nagl, 2024). Systematic error patterns, while not eliminated, are consistent and thus controllable in comparative studies.

To mitigate the black-box limitations, the analysis incorporates a triangulation approach: automated sentiment results were cross-validated using manual classification of selected subsets. This strengthens accuracy, particularly in mixed or ambiguous cases, and aligns with best practices in hybrid sentiment research (Rauchfleisch et al., 2023). Ultimately, machine-based results were augmented by human interpretation, improving content-specific insights and overall methodological robustness.

3.2. AI tool-based analysis

AI is increasingly recognized as a key driver of the Fourth Industrial Revolution (Krafft et al., 2020). In this study, AI, specifically ChatGPT (OpenAI, 2023), is employed to support analysis of the general acceptance and reputation of WtE incineration technology. Acceptance here is understood as stakeholders' willingness to adopt or support a technology (Linzenich et al., 2019). This aligns with studies showing that acceptance is often shaped by perceived usefulness, ease of use, and user attitudes (Sahu et al., 2021), which are also reflected in sentiment trends captured by AI.

ChatGPT functions not as a standalone analytical tool, but as a complementary method within a triangulated framework alongside opinion mining and manual content classification. This multi-method setup enhances robustness and interpretability by enabling cross-validation across human-coded insights, sentiment patterns, and AI-assisted thematic outputs. The use of ChatGPT is supported by its demonstrated strengths in natural language processing (Qin et al., 2023; Kocoń et al., 2023) and increasing relevance in socio-technical research (Daly et al., 2025).

The tool was applied across global, regional, and local measurement levels to surface perceptions, validate sentiment trends, and suggest narrative frames for deeper manual investigation. Its integration follows calls for responsible AI use in professional contexts (Lund and Wang, 2023) and builds on prior research highlighting its text analysis potential (Biswas, 2023; Bouschery et al., 2023; Haleem et al., 2022; van Dis et al., 2023).

While ChatGPT offers scalable text interpretation and has growing applications in sentiment analysis (Haque et al., 2022; Nakano and Yamaoka, 2023; Sudirjo et al., 2023), its current limitations are acknowledged. These include lack of statistical analysis capacity (Cascella et al., 2023), occasional reasoning gaps (Borji, 2023), a knowledge cutoff, in 2021, and a black-box architecture that restricts visibility into its training data and potential biases (Bouschery et al., 2023; Daly et al., 2025). Based on deep learning models that improve with training, ChatGPT represents a step beyond earlier NLP systems although limitations remain (Diwali et al., 2024; Lu et al., 2023; Wang et al., 2023).

Nonetheless, recent work (Xu et al., 2024) supports the use of explainable AI and multi-modal models to enhance sentiment classification trust. In this study, ChatGPT's outputs were interpreted as indicative rather than conclusive, and were cross-checked against both automated sentiment data and human-coded findings to ensure reliability and contextual fit.

By situating ChatGPT within a broader analytical framework, this study leverages its strengths while mitigating its weaknesses, ultimately enriching the empirical analysis of WtE-related stakeholder perceptions.

3.3. CA-GALT analysis

CA-GALT is a powerful statistical method designed to analyze complex datasets, particularly those involving textual and contextual variables that are not directly observable (Bécue-Bertaut and Pagès, 2015; Kostov et al., 2015). It extends classical Correspondence Analysis by integrating multiple quantitative, categorical, and mixed variables, making it highly suitable for analyzing media datasets addressing global environmental issues.

Generalized aggregated lexical tables are built by combining word frequencies across predefined textual units and linking them to relevant variables or categories. This process enables researchers to explore and visualize the semantic structure of large textual corpora, uncover associations between lexical patterns and metadata, and identify latent dimensions that organize the data (Breznik et al., 2024). In addition, incorporating external variables, such as environmental indicators or media narratives, reveals otherwise hidden patterns and relationships.

In this study, CA-GALT facilitates the identification of atypical or influential lexical patterns and associations, thereby guiding deeper qualitative interpretation and minimizing the risk of overlooking key insights. Specifically, it is applied to the WtE incinerator media dataset to cluster countries at the regional level based on the distribution of media hits. As a specialized form of Correspondence Analysis, CA-GALT projects entities (e.g., countries) onto a two-dimensional plane according to their lexical or categorical properties. This mapping supports the identification of regional patterns and highlights potential outliers that may warrant closer examination.

Although originally developed for textual data, CA-GALT is adaptable to broader datasets. It enhances interpretability by visually summarizing complex relationships in large-scale media content. Here, its application complements the overall triangulated methodology by contributing an additional layer of pattern recognition and regional differentiation.

3.4. Combination of different methods

The study employs a hybrid, three-step methodology that integrates large-scale computational techniques with human-based analysis, a model widely adopted in digital humanities (Nuortimo, 2021; Zamith and Lewis, 2015). Each method targets distinct knowledge domains, enabling a multi-scalar understanding of product reputation and stakeholder sentiment.

1) Large-Scale Analysis:

The first step involves opinion mining, AI-assisted analysis, and CA-GALT clustering to examine WtE incinerator discourse from a regional perspective (primarily Europe). Here, particularly negative sentiment clusters are flagged for closer inspection, aiding in the identification of possible corrective actions in product or marketing strategy.

2) Country-Level Focus:

In the second step, a selected product with the most impactful negative sentiment is examined at the national level to reveal geographic variation in perception and context-specific drivers of sentiment.

3) Manual Content Classification.

Finally, media hits are manually classified to extract nuanced insights into product reputation and public framing. This detailed review distinguishes between project-specific opposition, broader technology concerns, or brand-specific issues, thereby supporting tailored managerial responses.

The hybrid approach provides both macro-level comparisons and micro-level depth. It helps identify not only sentiment polarity but also the root causes behind reputational issues. The manually validated outputs can guide corrective action, inform targeted marketing interventions, and enhance internal decision-making regarding communication and resource allocation.

3.5. Measuring reputation & generating reputation score

In measuring reputation, the central question is: what product/technology attributes are intended to be projected, how effectively are they communicated, and how are they perceived by customers/stakeholders? Reputation reflects stakeholders' evaluation of perceived attributes such as quality, performance, reliability, ethical behavior, and market presence, core dimensions shaping public perception (Cavazos et al., 2023; Narasimhan and Schoenherr, 2012).

Traditionally, reputation is measured through surveys and interviews (e.g., Luoma-Aho, 2007). For example, reputation can be linked to intended actions, such as willingness to purchase, by correlating perception metrics with behavioral intent (T-Media, 2023). However, reputation analysis through large-scale media data and opinion mining introduces added complexity. Media content is often unstructured and may reflect conflicting narratives, requiring careful consideration of context and event sequences.

In the case of product reputation, challenges arise when expected attributes, such as affordability or delivery speed, are contradicted by sentiment trends in electronic word-of-mouth (eWOM) or online reviews. Prior research demonstrates that reputation analytics can uncover such misalignments, helping identify underperforming attributes and refine communication strategies (Lei et al., 2016; Farooq et al., 2016). These insights can inform corrective actions in product and marketing management.

Table 4
Likert scaling of reputation attributes.

Sentiment	Score
Very positive	5
Positive	4
Neutral	3
Negative	2
Very negative	1

To operationalize media-based reputation assessment, sentiment outputs are converted into Likert-style numerical values (Table 4). These are particularly useful when evaluating polarized sentiment, very positive and very negative, through combined automated and manual review.

These sentiment-derived scores form the basis for a computed reputation score, which can be benchmarked against traditional perception metrics such as survey-based ratings (e.g., T-Media, 2023). By triangulating automated sentiment analysis with human judgment in extreme sentiment cases (scores 4–5 and 1–2), the study increases reliability and interpretive depth.

In the next section, this structured methodology is applied to assess the reputation of generic WtE incinerator products, not linked to specific companies. This distinguishes the approach from brand-oriented marketing studies. Instead of predefined product reputation definitions, the analysis focuses on *projected and perceived* reputation, and its relationship to acceptance and local resistance dynamics.

4. Data-analysis results

The analysis is structured across three levels, Global, Regional, and Local, with findings presented accordingly.

4.1. Global level

An AI-assisted tool (ChatGPT) was applied to analyze global perspectives on WtE incinerators, focusing on five interrelated constructs: acceptance, reputation, trust, perception, and sentiment. The analysis revealed that these constructs are highly context-dependent, varying across regions and stakeholder groups.

Sentiment toward WtE incineration is shaped by factors such as environmental performance, public awareness, regulatory credibility, and technological developments. A detailed breakdown of AI-generated responses to global framing questions is provided in Appendix C (Table C.1), with a summary in Table 5.

Finding: At the global level, acceptance is contingent on environmental impact, local experience, and the availability of alternative waste management practices. Reputation reflects operational performance, which can either strengthen or erode trust. Trust is central, driven by perceptions of safety, transparency, and regulatory reliability. Sentiment, in turn, acts as a proxy for emotional tone, helping to interpret the underlying dynamics of acceptance and perception.

Positive media sentiment can promote awareness, build trust, and enhance acceptance. Conversely, negative sentiment, particularly in contexts of low transparency or historical controversy, may erode stakeholder confidence and hinder technology adoption.

Fig. 4 presents a conceptual influence pathway from media sentiment to public acceptance, outlining how changes in public awareness and perception influence stakeholder trust over time. The model incorporates feedback loops (e.g., acceptance shaping future sentiment), as well as moderating factors like regulatory strength and technological performance, and distinguishes between short-term and long-term effects.

Table 5
Summary of global AI-based assessment on WtE incinerators.

Construct	Global Summary
Acceptance	Varies by region; shaped by regulation, alternatives, and engagement
Reputation	Mixed; driven by environmental performance and stakeholder trust
Trust	Dynamic; influenced by transparency, safety record, and regulatory oversight
Perception	Contextual and evolving; shaped by awareness and media framing
Sentiment	Mixed globally; fluctuates by region and over time

4.2. Regional level

4.2.1. Sentiment analysis (regional)

To enable comparability across European contexts, a hybrid sentiment analysis approach was employed. The first stage utilized a commercial media monitoring tool (M-Brain) to classify sentiment in English-language media discussing WtE incinerators. English was selected for consistency, although this inevitably concentrated social media hits in English-speaking countries.

The initial product-group analysis focused on the keyword "Waste-to-energy incinerator" over a 16.5-month period (1 January 2020–18 May 2021), yielding 51,926 media hits. Sentiment was nearly evenly split, 44% positive and 42% negative, indicating a polarized public discourse. This reinforces the critical role of trust, perception, and transparency in shaping public acceptance.

Finding: The near parity in sentiment reflects a contested narrative around WtE technologies. The significant presence of negative sentiment highlights the need for multi-dimensional analysis and proactive stakeholder engagement.

On average, WtE incinerators receive relatively modest media attention, approximately 100 hits per month. The sentiment results align with prior literature and earlier opinion mining findings in energy technology contexts (Nuortimo and Harkonen, 2019b). Building on this, the second stage of the hybrid analysis focused on more granular country-level sentiment patterns (see Fig. 5).

Although English media allowed broad coverage, country-level analysis revealed variations in sentiment intensity. Negative sentiment percentages across selected countries based on English-language media are presented in Fig. 6.

Based on these results, the share of negative sentiment included: Finland (30%), Sweden (41%), Germany (32%), Spain (39%), the UK (42%), France (43%), and Ireland (47%).

To deepen the analysis, native-language search terms were used alongside distinctions between editorial and social media sources. This expanded coverage, particularly for social platforms, and enabled more nuanced interpretations of national and platform-specific discourse.

As shown in Table 6, notable variation emerged. Finland had the lowest proportion of negative sentiment in editorial media (8%), while France recorded the highest (50%). Spain's data was limited to editorial sources, whereas Finland and Sweden exhibited marked differences between editorial and social sentiment. These findings highlight the role of national context, language, and media type in shaping public perception.

Finding: National discourse around WtE incineration varies significantly across countries and media types. In some cases, editorial media is more positive than social media, while the reverse also occurs. These contrasts highlight the importance of local language strategies and mixed-method sentiment analysis.

The inclusion of local-language sources adjusted sentiment scores in several countries. A combined view of English and local-language media hits is presented in Fig. 7.

This country-level comparison showed that Sweden had a notable increase in social media coverage, much of it in the local language. Despite this, most WtE incineration-related media hits remained editorial in nature, suggesting relatively low social media engagement.

The UK showed the highest number of negative hits, offering a focal point for detailed analysis through manual classification and framing. At this stage, qualitative review and sentiment validation helped clarify the accuracy of automated outputs and explored whether negative coverage stemmed from product reputation, public risk perceptions, acceptance barriers, or local opposition. These insights inform both theoretical contributions and potential communication responses.

In several UK, French, and Finnish cases, opposition narratives referenced health risks, particularly cancer, respiratory illness, and dioxin exposure, often near residential areas, schools, or water sources. These concerns were amplified in regions with industrial legacies or

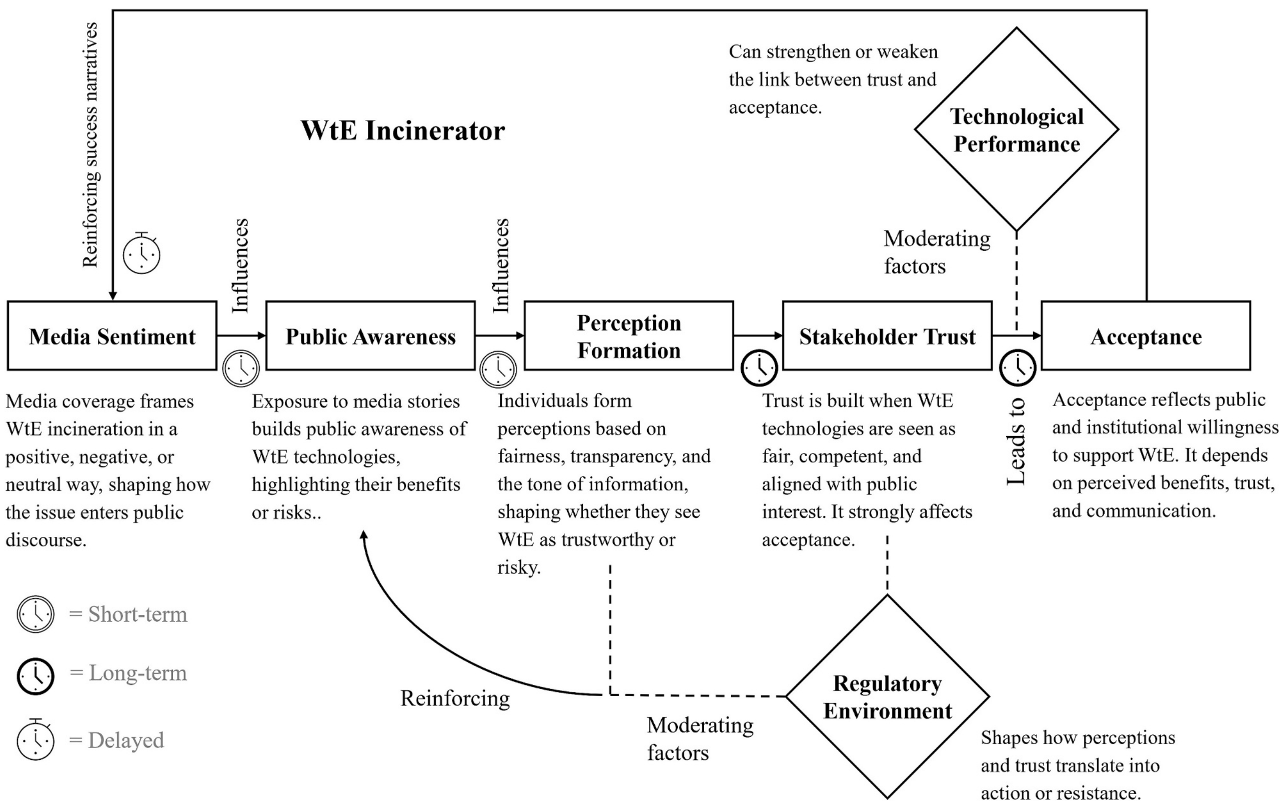

Fig. 4. Influence diagram illustrating the pathway from media sentiment to stakeholder trust and public acceptance of WtE incineration. Arrows indicate direction of influence; feedback loops show how outcomes reinforce media sentiment. Moderating factors and temporal dynamics are included.

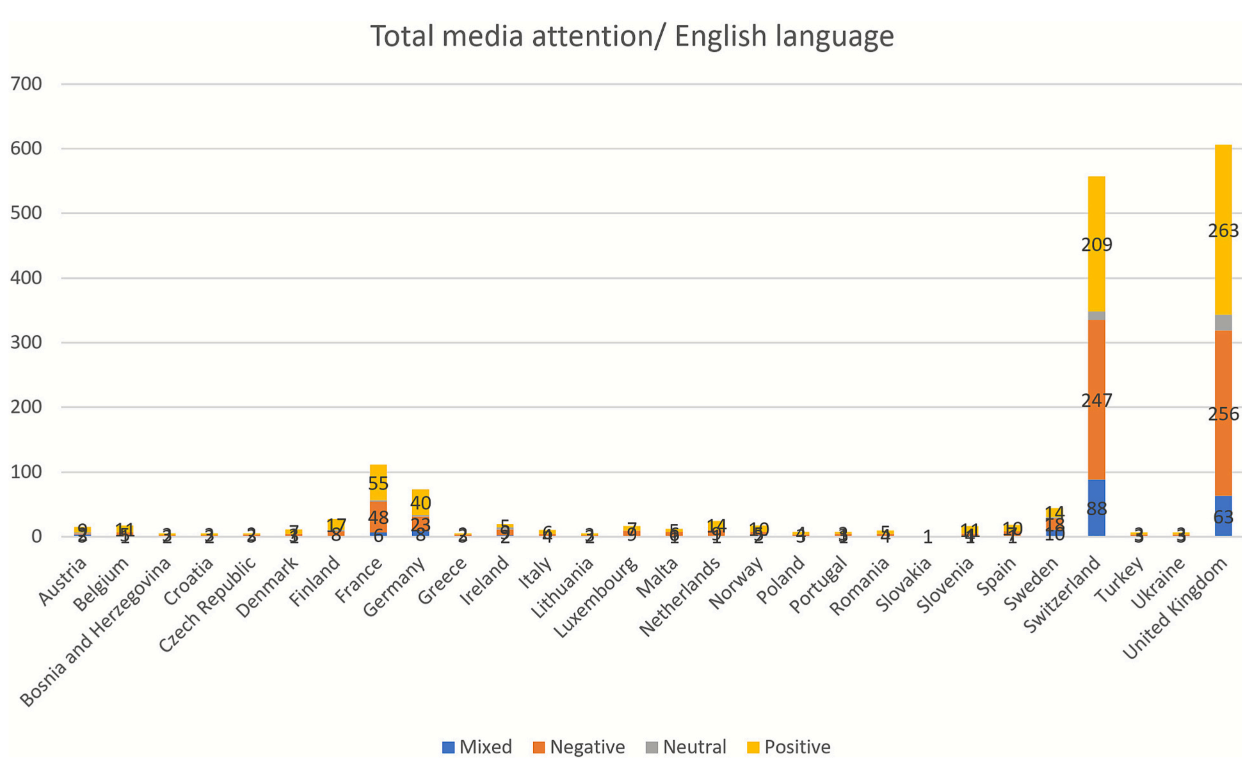

Fig. 5. English-language media attention toward WtE incinerators across European countries.

limited public consultation. In contrast, media in higher-trust municipalities (e.g., Finland, Sweden) emphasized emissions control, reliability, and climate compatibility, portraying WtE as a responsible waste management solution.

This contrast suggests that risk perception is shaped not just by technology performance but by socio-economic and institutional

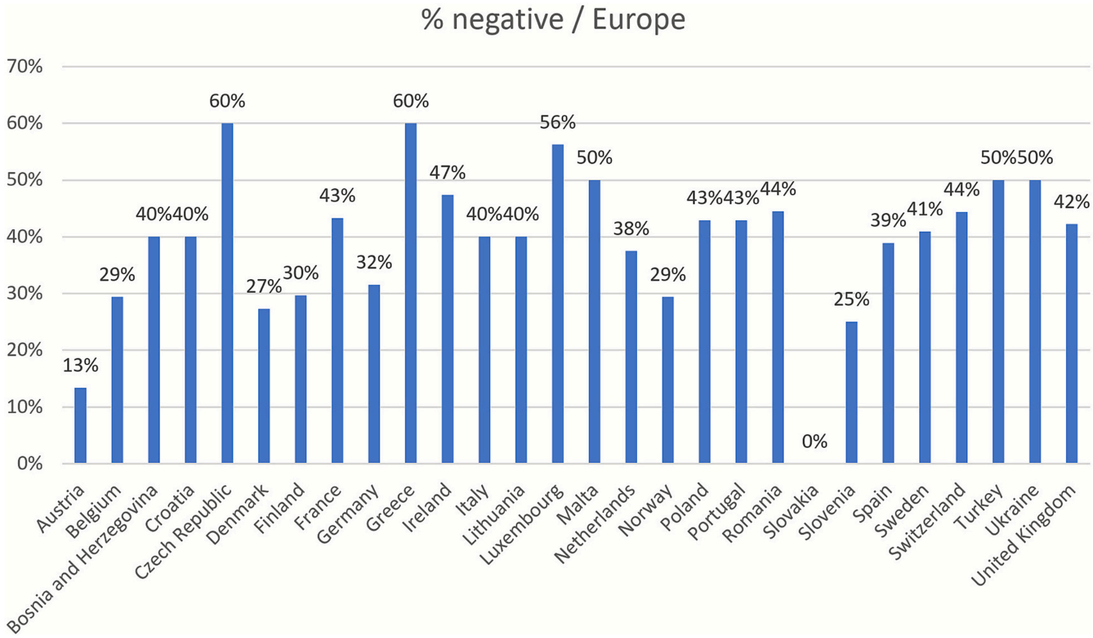

Fig. 6. Percentage of negative sentiments on WtE incinerators across European countries.

Table 6
Country-level sentiment analysis using local language search terms.

Country	Local language search words	Time frame	Hits in the local language	Editorial / Social Media Hits	% Negative hits on editorial / social media
Finland	"Jätteenpolttolaitos"	1.1.2020–15.6.2021	1006	742 / 264	8 / 21.6
Sweden	"Avfallsförbränning"	1.1.2020–16.6.2021	7168	5810 / 1358	28 / 12
Germany	"Abfallverbrennung"	1.1.2021–4.6.2021	356	289 / 67	10 / 0
Spain	"Planta de incineración de residuos"	1.1.2020–25.6.2021	91	91 / 0	42 / 0
France	"Installation d'incinération des déchets"	1.12020–11.6.2021	375	371 / 4	50 / 100 ($n = 4$)

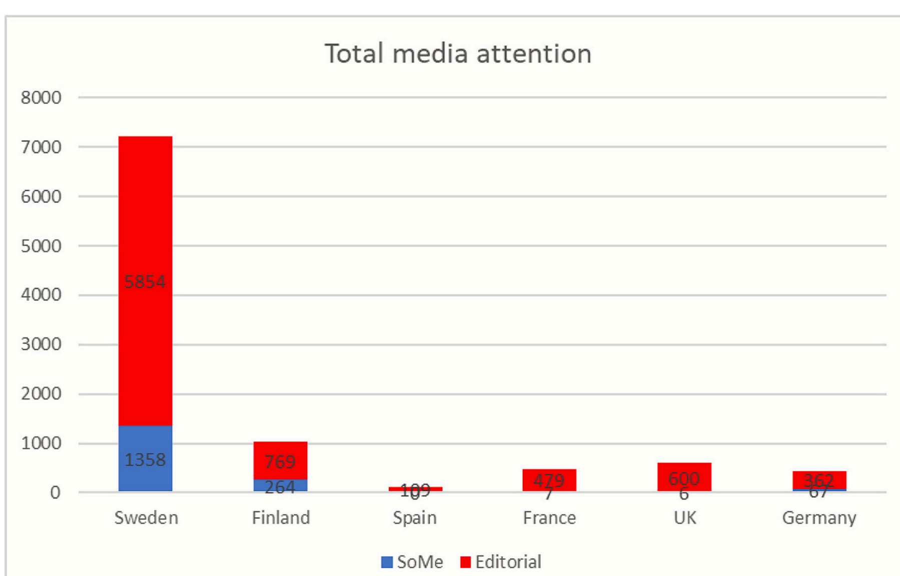

Fig. 7. Total media attention by country: English- and local-language scores.

context. In environments with higher institutional trust, WtE is more likely to be accepted as part of a long-term environmental strategy. In lower-trust settings, narratives may reflect broader concerns about fairness, transparency, and environmental justice.

4.2.2. AI tool-based analysis (regional)

To systematically assess public discourse on WtE incinerators across Europe, an AI-assisted analysis was conducted in 28 countries, focusing on five interrelated constructs: sentiment, acceptance, reputation, trust, and perception. The AI-generated outputs included both qualitative summaries and numerical scores on a 0–100 scale.

Results reveal notable cross-country variation. While most countries exhibited mixed sentiment and moderate trust, the Nordic countries, Sweden, Norway, and Denmark, consistently scored high across all five dimensions.

A detailed country-level breakdown is provided in Appendix D (Table D.1). A summary of key trends across the region is presented in Table 7 below.

Complete country-level scores and qualitative insights are provided in Appendix D (Table D.1).

Finding: Regional patterns of acceptance, reputation, and trust, offer insight into public motivations, perceived risks, and stakeholder concerns. These findings can guide tailored stakeholder engagement strategies by identifying where confidence is already high and where enhanced communication, transparency, or policy clarity may be required.

4.2.3. *CA-GALT analysis*

The CA-GALT method enables a multidimensional comparison of document-term matrices, here presented by a country-topic matrix, with regional-level AI tool outputs on sentiment, acceptance, reputation, trust, and perception. The method integrates frequency data with perceptual scores using (multiple) correspondence analysis to uncover latent structures in the data.

The CA-GALT results are visualized through three two-dimensional factor maps: Fig. 8 (countries/individuals); Fig. 9 (topics/frequencies); and Fig. 10 (perceptual constructs/categories).

In Fig. 9, topics tied to highly specific or expert-driven coverage (e.g., Sci.Res and Health.Well.b) appear prominently on the right side. By contrast, the left side displays a more diverse mix of economic and infrastructural themes (Bus.Fin, Tech.Comm, Energy), along with topics reflecting broader societal and policy issues (Polit.Soc, Environ.Nat, Food.Bev).

The horizontal dimension in Fig. 10 contrasts categories on the left—RepNeg, PerNeg, TruMod (negative representations, moderate trust) and SenMix, AccHigh (mixed sentiments, high accessibility)—with those on the right—RepPos, TruHigh, PerPos (positive representation, high trust) and AccLow, AccMod, SenPos, AccVar (lower but varied accessibility and positive sentiment). This polarity reflects a shift from critical/mixed discourse on the left to constructive/positive framing on the right.

The most relevant insights emerge when these visualizations are interpreted collectively. Countries located close to each other in Fig. 8 tend to share similar topic associations (Fig. 9) and perceptual profiles

Table 7
Summary of AI-Based perception constructs across 28 European countries.

Construct	Average Score (0–100)	Highest Scoring Countries	Lowest Scoring Countries
Sentiment	~48	Denmark (70), Norway (70), Sweden (70)	Austria (30), Greece (50), Luxembourg (50)
Acceptance	~47	Denmark (70), Norway (70), Sweden (70)	Iceland (30), Luxembourg (30), Malta (30)
Reputation	~51	Denmark (75), Norway (75), Germany (70),	Luxembourg (30), Malta (30)
Trust	~48	Germany (75), Norway (75), Sweden (75)	Greece (40), Poland (35), Romania (35)
Perception	~50	Denmark (75), Norway (75), Sweden (75)	Luxembourg (30), Malta (30), Hungary (45)

Note: Scores are interpreted as follows: 0–39 = low or negative, 40–59 = mixed or moderate, 60+ = positive or high.

(Fig. 10). Proximity in the individual factor map reflects both thematic and perceptual similarity.

Three main country clusters are identified:

Cluster 1 – *Switzerland* is isolated, characterized by positive sentiment and moderate acceptance, with discourse focused on *Science & Research* and *Health & Well-being.*

Cluster 2 – *United Kingdom, Italy, and Malta* form a group characterized by negative reputation and perception but moderate trust. Their discourse emphasizes *Travel & Vehicles, Entertainment & Hobbies, Politics & Society, Construction & Habitation*, and *Life & Living.*

Cluster 3 – The remaining countries cluster around topics like *Business & Finance, Technology & Communications*, and *Energy*, characterized by mixed sentiment and perception but high acceptance.

The analysis reveals meaningful differences in how European countries frame and report on WtE incineration in the media. The first (horizontal) dimension, which explains most of the variance, represents a polarity between generalized, socially grounded discourse on one side and specialized, technically focused discourse on the other.

The United Kingdom, Italy, and Malta appear on the lower-left of Fig. 9. Their media coverage is tied to topics like politics, environment, and social issues, often framed through a critical lens with negative or mixed evaluations, moderate trust levels, and more emotionally varied tones.

In contrast, *Switzerland* and *Finland* appear on the right of the first dimension. Their position reflects a distinct media pattern emphasizing scientific research and health-related themes. These countries show positive representations, high institutional trust, and lower emotional intensity, indicating expert-driven and technically framed discourse. Notably, *Switzerland* emerges as a strong outlier, suggesting particularly professionalized and depoliticized coverage.

Countries near the center of the factor map, such as *Germany, France*, the *Netherlands*, and several Central and Eastern European nations (e.g., *Slovenia* and the *Czech Republic*), may represent more balanced or mixed media landscapes. They show no extreme associations with specific themes or framing patterns, possibly reflecting a diversity of viewpoints or neutral reporting styles.

Overall, CA-GALT highlights how European countries differ not only in the topics emphasized in WtE coverage but also in the framing of that coverage—ranging from politically contested and socially embedded narratives to scientifically oriented, institutionally aligned discourse.

Highlight: The CA-GALT triangulation provides a rich interpretive layer by linking public discourse topics with regional variations in perception, trust, reputation, and acceptance. This approach offers valuable insights for academic research and policymaking, enabling more targeted communication and stakeholder engagement strategies

4.3. *Local level*

4.3.1. *Manual content classification analysis*

To better understand the drivers of positive and negative sentiment toward WtE incinerators, a manual media classification was conducted at the country level, focusing on the UK. Out of 606 total media hits, a random sample of 50 articles was manually reviewed to assess both topic relevance and the accuracy of automated sentiment tagging.

The results showed that 62% (31/50) of the articles were correctly classified in terms of both sentiment and relevance, emphasizing the value of interpretive review, especially for complex, context-sensitive technologies like WtE incineration. Manual classification also helped uncover specific concerns behind negative sentiment, offering insights for targeted communication and stakeholder engagement.

In the reviewed dataset (n = 50), 30% of hits concerned product reputation, and 28% referenced local resistance. However, only 24% (12/50) were both sentimentally accurate and theoretically relevant for

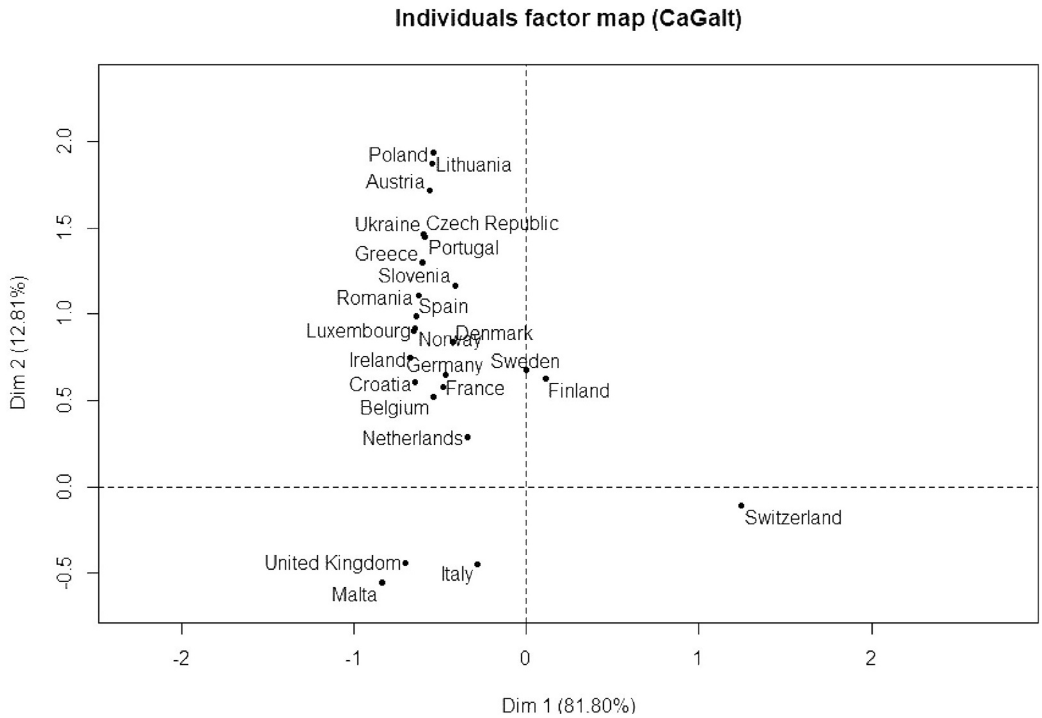

Fig. 8. CA-GALT: Countries (individuals).

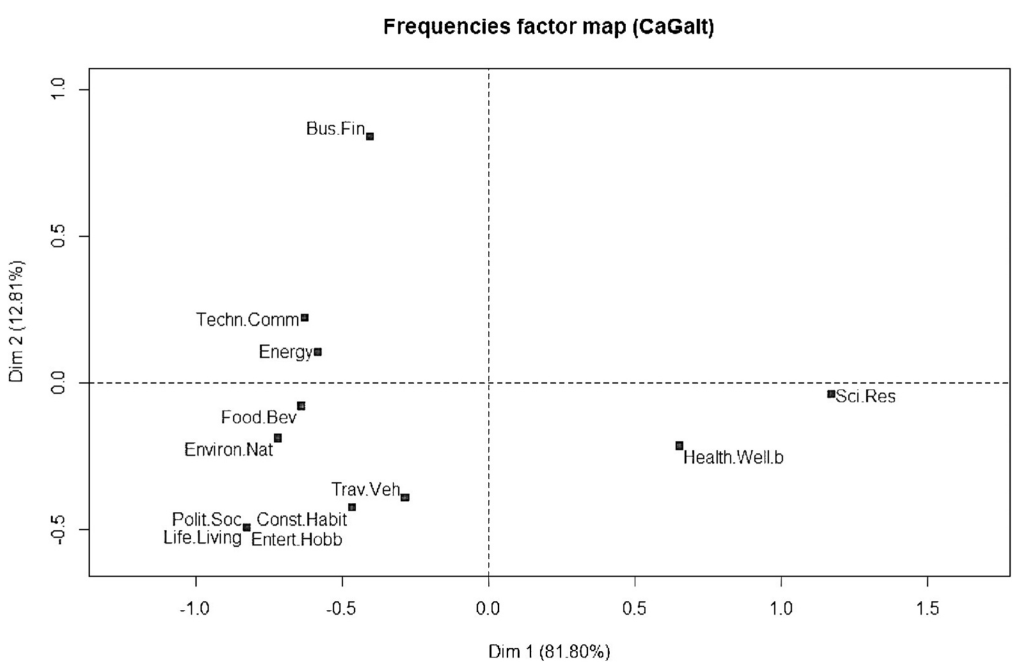

Fig. 9. CA-GALT: Topics (frequencies).

measuring reputation. Of these, 9 were negative, and only 2 were positive, suggesting a dominance of negative framing in reputation-related discourse.

These results reinforce the utility of a hybrid approach, combining automated sentiment tools with selective manual validation. While machine analysis offers scalable insights, it should be interpreted as indicative rather than definitive. Manual review provides depth and helps inform corrective action, particularly in contexts where stakeholder sentiment and public reputation are critical.

To further illustrate how individual media narratives relate to product reputation, a targeted manual analysis of 14 selected media hits was conducted (see Appendix E, Table E.1). Each article was assessed for sentiment accuracy (machine vs. manual), relevance, and reputational framing. Eight articles were considered reputation-relevant, and 6 were correctly tagged by the automated system. Using a 1–5 Likert scale, the average score was 2, indicating predominantly negative tone, driven by concerns such as local resistance, environmental risk, and controversy.

Finding: A basic reputation score, derived from Likert-scaled media items, provides an indicative way to assess reputation. Though not a replacement for surveys or interviews, it supports triangulation with

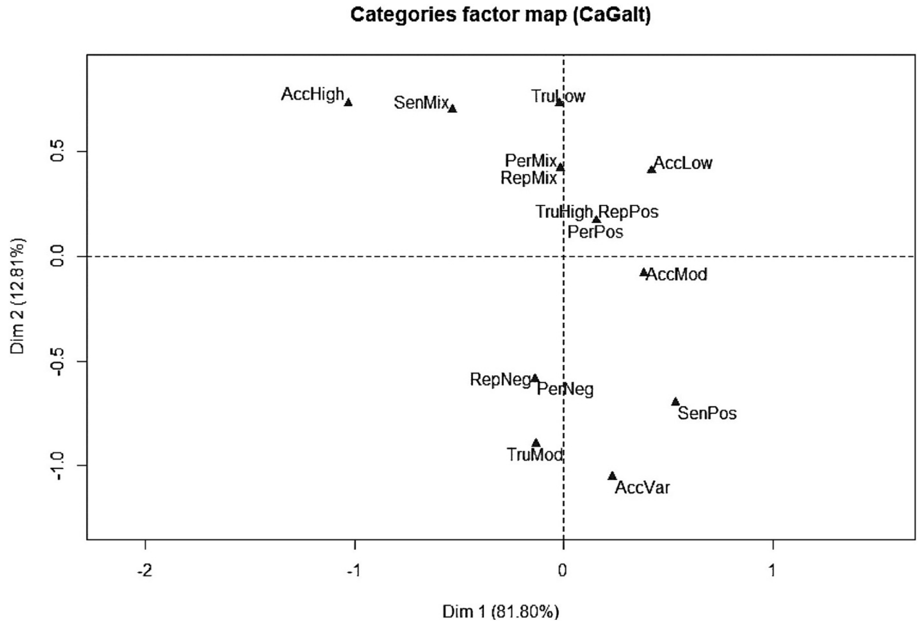

Fig. 10. CA-GALT: Perceptional constructs (categories).

structured stakeholder data.

Based on the thematic analysis, key reputation-related concerns were identified and mapped to marketing communication strategies and product design implications (Table 8). This supports alignment between stakeholder messaging, innovation, and project planning.

The sentiment and framing analysis revealed a polarized discourse. Negative sentiment clustered around themes such as health risks ("toxins," "cancer"), technological skepticism ("obsolete," "inefficient"), and procedural grievances (e.g., poor consultation). Conversely, positive sentiment was linked to energy recovery, climate compatibility, and compliance with modern standards.

Table 8
The main topical findings on the product reputation and local resistance.

Main reputation concern / effect	Recommended positive marketing messaging	Implications for product development/ improvement
Health-risk perception (toxins, dioxins, cancer)	Emphasize risk-mitigating design features; reference EU emission standards and burner regulations	Integrate health mitigating features into system design (e.g., advanced filtration, low-emission combustion).
Climate pollution concerns ("as polluting as coal", CO_2 emissions)	Highlight that waste displaces fossil fuels; stress low-carbon/biogenic components in waste streams.	Implement state-of-the-art pollution control; consider CCS/ CCUS integration.
Desire for cleaner, more efficient incinerators	Promote high-efficiency designs and cutting-edge technology.	Optimize combustion and energy recovery systems; include ash treatment technologies.
Local resistance (procedural injustice, NIMBYism)	Strengthen local communication; engage in inclusive planning and social marketing.	Foster participatory design and site-specific adaptations; support procedural fairness in siting.
Perceived economic inequity (profits vs. local impact)	Emphasize local benefits: job creation, revenue-sharing, infrastructure reinvestment.	Develop benefit-sharing mechanisms (e.g., energy discounts, shared ownership, municipal returns); ensure financial transparency.
Landfilling Comparison (methane emissions)	Frame incineration as a cleaner alternative to landfilling (methane reduction).	No direct design implication unless feature-specific resistance emerges.

This contrast illustrates the dual influence of perceived risk and benefit in shaping public attitudes. Moreover, NIMBY-type opposition shows that even technically sound projects can face pushback where transparency, fairness, or local agency are perceived as lacking.

4.3.2. *AI tool-based analysis (local)*

To complement national-level findings, a city-specific analysis was conducted to explore how acceptance, reputation, and trust toward WtE incinerators manifest in selected European capitals. These cities were selected due to their prominence in shaping national discourse and policy.

As summarized in Table 9, Stockholm and Helsinki display consistently high levels of acceptance and trust, reflecting alignment with strong national WtE strategies and institutional credibility. In contrast, Madrid, Paris, and London exhibit mixed or negative perceptions, mirroring broader skepticism and public resistance. Berlin presents a distinctive profile: despite only moderate acceptance, the city maintains relatively high levels of reputation and trust, potentially attributable to technological maturity and robust regulatory frameworks.

5. Discussion

Global waste management challenges require consideration of less-preferred methods in the waste hierarchy, such as waste-to-energy (WtE) incineration. These approaches demand greater attention to stakeholder engagement and informed decision-making. Understanding and (even if only) indicatively measuring product and technology acceptance, reputation, and trust is essential for guiding these efforts. This study focuses on WtE incineration, which serves as an alternative to landfilling while producing electricity or heat, yet often faces

Table 9
Local acceptance, reputation, and trust in selected capital cities.

Capital city	Acceptance	Reputation	Trust
Stockholm, Sweden	Generally positive	Generally positive	Relatively high
Helsinki, Finland	Generally positive	Generally positive	Relatively high
Madrid, Spain	Negative	Mixed	Varies
Paris, France	Moderate	Mixed	Varies
London, UK	Moderate	Mixed	Varies
Berlin, Germany	Moderate	Generally Positive	Relatively high

reputational challenges and local resistance due to concerns about emissions and resource competition.

By applying a hybrid methodology across knowledge domains, this study provides a comprehensive view of WtE-related acceptance, trust, and reputation. These constructs are tightly interlinked: trust and reputation shape acceptance, and acceptance, in turn, influences both. Negative experiences can erode trust and reputation, thereby reducing acceptance. Perception plays a crucial role in this dynamic: reputation can be understood as the aggregate of stakeholder perceptions, which also shape trust. Measuring reputation thus entails assessing perception, which ultimately affects policy, regulation, and market deployment for technologies like WtE.

Understanding these dynamics lays the groundwork for effective stakeholder engagement and strategic decision-making. Indicative measurement using sentiment analysis and AI-assisted tools enables assessment of acceptance, reputation, and trust at global, regional, and local levels. Media coverage significantly shapes public perception and plays a key role in fostering acceptance or resistance. In ESG and sustainable technology contexts, AI-based sentiment analysis has shown how emotional factors such as trust, fairness, and governance transparency strongly influence stakeholder acceptance (Jaiswal et al., 2025). Higher acceptance fosters political support and funding, facilitating broader market adoption.

Trust is especially critical. It is tied to perceptions of safety, quality, and credibility, and varies across contexts. Evidence from AI adoption research shows that trust is not uniformly fragile, but depends on perceived competence and domain sensitivity, remaining strong in technical areas and weaker in value-laden ones (Bao et al., 2025). WtE incineration appears to follow similar patterns. Furthermore, positive social media sentiment may not translate into reputational gains unless an organization already enjoys a strong reputation (Islam et al., 2025), highlighting the need to build credibility proactively.

At the *global level,* WtE acceptance, trust, and reputation vary by geography, regulatory environment, and technology context. These factors evolve alongside advances in technology, shifting risk perceptions, and emerging alternatives. *Regional-level* analysis provides insight into country-specific motivations and stakeholder concerns, supporting more targeted stakeholder engagement strategies. The value of *local-level* analysis lies in capturing project-specific perspectives, enabling tailored communication and more effective responses to local opposition.

The interdisciplinary approach of this study reveals insights that single-discipline methods may overlook. For example, combining AI-driven sentiment analysis with stakeholder theory highlights the impact of fairness and transparency on public trust. Similarly, integrating environmental risk theory with media classification uncovers how socio-economic contexts shape resistance to WtE incineration. These insights are particularly important for waste management, where public acceptance is shaped not only by technical factors but also by emotional, social, and political dimensions.

Moreover, digital discourse often reflects emotionally charged, politically influenced sentiment rather than carefully reasoned stakeholder opinion (Kim et al., 2024), warranting caution in interpretation. While earlier studies (e.g., Liu et al., 2019; Cole-Hunter et al., 2020) focused primarily on emissions and health concerns through expert assessments, this study highlights additional themes such as procedural fairness, economic justice, and institutional trust, echoing findings from recent narrative framing research (Tan et al., 2025).

In contrast to Muscio et al. (2023), who emphasize structural and regulatory barriers to WtE deployment, this study highlights perception-driven resistance rooted in emotional narratives. Traditional technology acceptance models (e.g., Venkatesh and Bala, 2008) focus on cognitive aspects like perceived usefulness and ease of use. In contrast, our AI-assisted approach reveals deeper, contextual dynamics including distrust, fear, and fairness. Similar trends have been observed in ESG-related sentiment research, where resistance stems from perceived ethical deficiencies despite technical merits (Jaiswal et al., 2025). This calls for a broader, multidimensional understanding of technology acceptance, one that integrates cognitive, emotional, and contextual perspectives (Wang et al., 2025).

These dynamics are synthesized in Fig. 4, which maps the influence pathway from media sentiment to stakeholder trust and public acceptance. The diagram captures feedback loops and moderating factors such as regulatory context and technical performance. Importantly, it also reflects the temporal dimension of these relationships: while media sentiment can swiftly shift public perception, the formation of trust and acceptance unfolds more gradually, through repeated exposure, institutional conduct, and experiential learning. This helps explain why short-term shifts in sentiment may not lead to immediate behavior change, but can still lay the groundwork for long-term transformation in public attitudes and policy outcomes.

5.1. Summary of contributions

This study makes contributions at three levels:

1. Theoretical: It extends technology acceptance theory by integrating emotional, trust-based, and fairness-related constructs into WtE acceptance, and demonstrates how AI-assisted discourse analysis can capture these dynamics beyond survey-based approaches.
2. Methodological: It introduces a hybrid AI–media-sentiment approach as a scalable, triangulated complement to traditional acceptance studies, validated across global, regional, and local levels.
3. Practical/Policy: It provides municipalities, operators, and regulators with a structured framework to anticipate stakeholder resistance, design engagement strategies, and enhance the social license to operate in contested infrastructure projects.

5.2. Theoretical interpretation of results

To our knowledge, this is the first study to demonstrate, through large-scale AI-based sentiment and discourse analysis, how constructs from TAM and UTAUT manifest in real-world public discourse on environmental technologies. While earlier acceptance studies relied primarily on surveys or interviews (e.g., Liu et al., 2019; Venkatesh and Bala, 2008; Blut et al., 2022), our approach captures contextualized, large-scale narratives that link directly to perceived risk, trust, and performance expectancy. For example, media concerns about “toxins,” “pollution,” and “health risks” reflect perceived risk theory (Weber et al., 1992) and are associated with reduced competence- and integrity-based trust (McKnight et al., 2002). By contrast, narratives emphasizing “climate neutrality” and “waste reduction” correspond to high perceived usefulness and performance expectancy in TAM and UTAUT.

Cross-national patterns indicate that acceptance tends to be higher in contexts of strong institutional trust (Siegrist and Cvetkovich, 2000), while heightened opposition in lower-income communities highlights the role of procedural justice (Walker, 2012), where perceptions of fairness strongly shape trust and acceptance.

This integration of theory and findings clarifies how technical features, socio-political context, and emotionally framed narratives jointly influence public acceptance of WtE technologies. These connections between public discourse and theory-grounded constructs establish a foundation for rethinking how acceptance, trust, and reputation are conceptualized in socio-technical systems.

5.3. Theoretical implications

The primary theoretical contribution of this study lies in the integration of multiple methodological approaches, including AI-assisted sentiment analysis and discourse mining, to assess acceptance, trust, and reputation in relation to WtE incineration across global, regional, and local levels. The novel application of AI-based analytical tools enables scalable, real-time monitoring of stakeholder sentiment, explicitly complementing traditional survey- and interview-based methods.

Beyond extending TAM and UTAUT, this study makes a novel theoretical contribution by showing how constructs such as fairness, trust, and emotional resistance manifest in large-scale public discourse, dimensions that prior acceptance studies, largely reliant on surveys or interviews (e.g., Liu et al., 2019; Venkatesh and Bala, 2008; Blut et al., 2022), have rarely captured at scale. Empirically, the findings demonstrate how public narratives emphasize both risk-related concerns (toxins, health risks, emissions) and benefit-oriented themes (energy recovery, waste reduction). Consistent with perceived risk theory (Weber et al., 1992) and trust theory (McKnight et al., 2002), the results confirm that trust mediates the relationship between risk perception and acceptance, as also argued by Siegrist and Cvetkovich (2000). By embedding both classical acceptance constructs and these additional dimensions into discourse-based analysis, this study enriches acceptance theory and establishes new avenues for applying it in contested infrastructure contexts such as WtE.

Recent evidence from blockchain adoption (Adaryani et al., 2024) emphasizes how trust amplifies perceived performance benefits, reinforcing its contextual relevance for controversial technologies like WtE. These findings also respond to critiques of UTAUT's generalizability (see Blut et al., 2022), suggesting that trust, fairness, and risk perception should be integrated into acceptance theory in socio-technical domains. This aligns with findings from other infrastructure megaprojects, such as hydropower, where external social responsibility has been shown to foster public trust and community acceptance (Aga and Beyene, 2025). Similarly, recent studies reveal that perceived organizational legitimacy mediates the relationship between CSR intensity and stakeholder assessments of reputation (Shahid, 2025), reinforcing legitimacy theory and advancing a relational, nonlinear understanding of acceptance.

The study also emphasizes the critical role of institutional trust and procedural justice, particularly perceptions of fairness in decision-making and siting, in shaping public perception and community response. These insights contribute to the socio-political understanding of technology acceptance, especially in regions marked by economic inequality or environmental legacy issues.

In addition, this study contributes to the waste management literature (Cole-Hunter et al., 2020; Liu et al., 2019; Muscio et al., 2023) by demonstrating how AI-assisted discourse tools can enrich acceptance studies and inform policy design. The proposed indicative reputation score complements the “stairs of acceptance” model (Nuortimo and Harkonen, 2022), providing a quantifiable proxy for tracking cumulative perception over time. Thus, this research not only affirms existing theoretical constructs but also operationalizes them through novel, real-world tools for WtE deployment strategy.

Finally, this study illustrates the value of interdisciplinary integration. By combining AI analytics, media sentiment analysis, and trust/acceptance theory, it provides a more comprehensive framework for understanding WtE deployment. This integration advances theoretical understanding in areas such as institutional trust, perceived fairness, and behavioral intention, particularly in contested infrastructure contexts.

5.4. Methodological implications

The findings demonstrate that indicative assessments of acceptance, trust, and reputation can be derived from media sentiment analysis and AI-assisted tools. The outputs from the AI tool and media monitoring software show strong convergence, suggesting a shared underlying logic, thereby offering a validation point for previous opinion mining research. While the AI tool provides broad, generalized assessments, it is less effective at capturing temporal shifts than the media monitoring software. Nonetheless, it offers a stable baseline for measuring sentiment and perceptual constructs across global, regional, and local levels.

A key methodological contribution of this study is its triangulated, multi-layered approach, combining automated sentiment analysis, media discourse review, and manual media content classification. This hybrid method captures nuanced perception drivers (e.g., health risks, fairness, transparency) that conventional survey techniques often overlook. It is particularly useful in infrastructure-related technology contexts, where stakeholder sentiment is dynamic and geographically variable.

Although access to real-time or longitudinal data remains a limitation, the AI-assisted tool's ability to assign perceptual scores and trace reasoning patterns presents new opportunities for strategic monitoring. These capabilities are especially valuable for market intelligence and risk communication. Furthermore, the CA-GALT method enriches the framework by revealing country-level variations and informing more focused analyses.

Overall, the methodology shows that AI-enhanced tools can effectively complement, and in some cases, partially substitute, resource-intensive primary data collection. This opens new, scalable pathways for studying public acceptance, trust, and reputation in the deployment of environmental technologies.

5.5. Managerial implications

This study highlights the potential of AI-assisted tools to provide timely, structured insights into public acceptance, reputation, and trust related to WtE incineration across diverse stakeholder groups and geographic contexts. These tools can support strategic communication, site selection, and engagement planning by detecting early signals of resistance or opportunities for positive messaging. However, each application must be validated on a case-by-case basis, taking into account local sensitivities, data availability, and stakeholder diversity.

Stakeholders involved in WtE development, such as municipalities, operators, and technology suppliers, can gain actionable insights into the reasoning behind public sentiment. Findings suggest that health concerns, procedural fairness (e.g., transparency, consultation), and perceived economic justice (e.g., local benefits vs. external profits) frequently underpin opposition narratives. Proactively addressing these themes in project design, communication, and benefit-sharing can reduce conflict risk and foster stakeholder alignment.

The proposed sentiment- and reputation-tracking framework also offers a practical complement to conventional survey-based monitoring. Integrating these insights into marketing, public relations, and planning processes may strengthen trust-building efforts and enhance the social license to operate.

Although centered on WtE incineration, the insights are transferable to other contested infrastructure technologies (e.g., carbon capture and storage, hydrogen, nuclear), where emotional narratives and fairness perceptions similarly influence acceptance. By demonstrating this wider applicability, the study broadens the generalizability of its managerial contributions and provides a reference point for stakeholder engagement across multiple socio-technical domains.

Beyond managerial use, the tools and insights also support evidence-based policymaking. By identifying areas of concern and tailoring outreach strategies early, they enable more proactive governance in deploying contested technologies like WtE incinerators.

6. Conclusions

This study offers a multi-method investigation into the acceptance, reputation, and trust surrounding WtE incineration by triangulating opinion mining, AI-assisted interpretation, CA-GALT clustering, and manual classification. The integration of digital discourse analysis with stakeholder sentiment mapping has proven both methodologically robust and theoretically insightful.

From a theoretical standpoint, the study extends established technology acceptance models (TAM/UTAUT) by incorporating risk perception, institutional trust, and procedural fairness, as well as trust and reputation as dynamic, sentiment-sensitive constructs. By capturing fairness, trust, and emotional narratives directly from large-scale public discourse, dimensions often overlooked in survey-based approaches, the study strengthens the theoretical grounding of acceptance research in contested infrastructures.

Methodologically, the study demonstrates how AI-assisted sentiment and discourse tools can enable scalable, real-time monitoring of public attitudes. ChatGPT-based interpretation uncovered emergent themes often missed by conventional methods, while CA-GALT clustering revealed latent, country-level structures in reputational dynamics. Cross-validating AI outputs with manual coding enhanced both the reliability and interpretive richness of the findings, effectively bridging algorithmic breadth with human judgment.

Empirically, the results reveal regional variation in sentiment that aligns with perceived legitimacy and trust, while also showing how digital trust markers, such as media framing and online discourse, mediate acceptance across contexts. Together, these findings reinforce that public acceptance is influenced not only by technical or environmental considerations but also by socio-political narratives and evolving digital discourse, making it possible to operationalize acceptance, trust, and reputation in ways that inform both scholarly frameworks and stakeholder engagement strategies across scales.

Taken together, this research highlights the value of a multidisciplinary approach, integrating AI analytics, stakeholder theory, media discourse, and environmental risk perspectives to capture the socio-technical complexity of WtE acceptance. The convergence of these domains enhances both the credibility and explanatory depth of the results.

Several limitations warrant acknowledgment. The commercial sentiment analysis tool used is a validated system with non-transparent ("black-box") algorithms. The analysis was limited to English-language content, potentially excluding culturally specific framings. Additionally, ChatGPT's insights are bounded by its training data and knowledge cutoff. While triangulation mitigated some of these limitations, they nonetheless define the methodological boundaries of this study.

Future research should apply this framework to other contested environmental technologies, such as carbon capture, hydrogen fuel, or nuclear energy, to examine the generalizability of sentiment–trust dynamics. Stakeholder-specific modeling (e.g., for citizens, policymakers, or NGOs) could further illuminate differentiated trust pathways. Lastly, the evolving domain of explainable AI holds promise for enhancing transparency and accountability in public-facing infrastructure discourse.

CRediT authorship contribution statement

Kalle Nuortimo: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Janne Härkönen:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Kristijan Breznik:** Writing – review & editing, Methodology, Formal analysis.

Appendix A

Table A.1
Avenues of perception affecting energy technology policies, legal and regulatory frameworks, and market deployment.

Perception can affect energy technology policies by impacting public opinion, stakeholder engagement, and decision-making by:	Perception can affect energy technology legal & regulatory framework through the perception by the public, policymakers, and stakeholders and impact the development of laws, regulations, and policies by:	Perception can affect energy technology market deployment by affecting the speed, scale, and success of the efforts by:
Affecting public acceptance (Sütterlin and Siegrist, 2017). Affecting investment decisions (Rockstuhl et al., 2021; Sachs et al., 2019).	Affecting policy priorities (Cotton and Charnley-Parry, 2018; Johansen, 2021)	Potentially affecting market acceptance (Wüstenhagen et al., 2007).
Public sentiment affecting politics and policies, subsidies, and funding (Hughes and Urpelainen, 2015).	Affecting regulations (Alrashoud and Tokimatsu, 2019) and result in supportive incentives, subsidies, or tax benefits. Potentially affecting incentive programs (Stern, 2014).	Affecting how well the technology attracts investment (Vaillancourt et al., 2008).
Affecting market demand (Yang et al., 2022).	Affecting the time taken by regulatory approval (Nielsen, 2022)	Affecting the viability of business models (Janipour et al., 2023).
Influencing regulatory frameworks (Sidortsov, 2014).	Affecting involvement by the public and their engagement (Peterson et al., 2015).	Affecting the adoption speed (Guta, 2018).
Affecting R&D, and innovation funding (Dreyer et al., 2017).	Affecting risk assessment requirements (Mousavi et al., 2022).	Affecting policies and regulations (Hughes and Urpelainen, 2015).
Affecting collaboration (Gaede and Rowlands, 2018), policy alignment, and agreements.	Affecting environmental impact assessment (Upham and Shackley, 2006).	Affecting public awareness and their engagement (Peterson et al., 2015). Affecting stakeholders' interests (Kahlor et al., 2020).
Media appearance and information sharing, and the resulting perception shaping public opinion and influencing policy decisions (Jiang et al., 2022; Stephens et al., 2008).	Affecting the location of the sites (Devine-Wright, 2008). Affecting deployment (Stephens et al., 2008) and commercialization.	May affect resistance, deployment, and market entry (Stephens et al., 2008). Affecting the realization of demonstration projects (Boyd et al., 2013).
Causing the NIBMY (Not-In-My-Backyard) effect, leading to zoning and permitting challenges and affecting energy technology deployment (Severnini, 2023).	Affecting health and safety regulations (Hammond and O'Grady, 2017). Affecting technology-specific regulations (Ozcan, 2016).	Leading to a Technological lock-in (Cecere et al., 2014).
Affecting long-term planning of energy technologies (Braunreiter and Bennett, 2017; Moallemi and Malekpour, 2018).	Affecting stakeholders' interest in information about the technology's development, potential risks, and benefits (Kahlor et al., 2020).	Positive perception toward the technology contributing to an innovation ecosystem (Kukk et al., 2015).
Affecting behavior by for example changing energy consumption habits (Liu et al., 2023).	Leading to public opposition and resistance (Stephens et al., 2008). Affecting international cooperation & agreements (Datta et al., 2020).	Affecting public support (Liu et al., 2017). Affecting funding (Hughes and Urpelainen, 2015).

Appendix B

Table B.1
Mapping theoretical constructs to operational definitions, data sources, and measurement methods.

Construct	Key attributes	Operational definition in study	Data sources & measurement methods
Trust	Competence, integrity, benevolence	Degree of stakeholder confidence in WtE incinerators and implementing actors (e.g., operators, regulators)	- Sentiment polarity and tone from news & social media - ChatGPT-assisted classification of trust-related expressions (e.g., "safe," "accountable") - Manual tagging of trust-indicative phrases
Reputation	Accumulated public evaluation over time	Generalized public and stakeholder appraisal of WtE technologies and institutions	- CA-GALT cluster analysis of discourse - Historical sentiment scores - Mentions of technology quality, responsibility, and innovation
Perception	Evolving stakeholder viewpoints	Stakeholder-specific understanding and framing of WtE, including risk-benefit trade-offs, fairness, and alignment	- Opinion mining and segmented sentiment tracking - ChatGPT-based narrative classification - Temporal shifts in perception across scales
Acceptance	Behavioral intention to support or adopt	Willingness of public/stakeholders to endorse, support, or resist WtE technology deployment	- Sentiment/discourse analysis (support/resistance) - Manual classification of pro/anti-incineration narratives - CA-GALT framing linked to deployment terms

Appendix C

Table C.1
AI Tool-based global acceptance, reputation, trust, perception, and sentiment.

Query	Response	Key points to consider
What is the global reputation of Waste-to-Energy Incinerators?	"The global reputation of WtE incinerators is a subject of debate and can vary significantly depending on various factors, including location, technology, and public perception." "Advances in technology and improved regulatory oversight have the potential to enhance the reputation by addressing some of the concerns. Public perception and community engagement also play a crucial role in shaping how these facilities are viewed in different regions."	- Environmental impact - Health Concerns - Technological Advances - Waste Management Alternatives - Public Perception - Regulatory Environment - Evaluation on a Case-by-Case Basis
How is the global reputation of waste-to-energy incinerators?	"The global reputation of WtE incinerators is mixed and can vary widely depending on geographic location, public perception, regulatory frameworks, and specific operational practices." "The reputation of WtE incinerators can change over time as technology improves and as communities become more informed about the benefits and potential risks associated with these facilities."	- Waste reduction (+) - Energy Generation (+) - Land Use (+) - Environmental Concerns (−) - Health Concerns (−) - Public Opposition (−) - Resource Competition (−) - Technological Advances - Regulatory Oversight - Local Context - Alternative Waste Management Strategies
What is the global acceptance of waste-to-energy incinerators?	"The global acceptance of WtE incinerators varies widely depending on geographical, cultural, and socio-economic factors. Acceptance or opposition to WtE incinerators is often influenced by a range of factors, including environmental concerns, public perception, regulatory frameworks, and the specific context of each community or region." "Essential to recognize that the acceptance of WtE incineration is highly context-dependent, and opinions can vary widely" "Public awareness, education, and engagement efforts can play a crucial role in shaping perceptions and acceptance levels. Additionally, developments in WtE technology and changes in waste management practices can influence the global acceptance over time."	- Acceptance varies by region - Perception can vary over time and affect acceptance - Alternative solutions can affect acceptance - Regulatory Influence - Community Acceptance can be improved via communication
How is the global acceptance of waste-to-energy incinerators?	"The global acceptance of WtE incinerators remains a complex and context-dependent issue. It varies widely from one region or country to another, and even within specific communities. Several factors influence the level of acceptance or opposition"	-Environmental and Health Concerns - Community Engagement - Regulatory Frameworks - Alternative Waste Management Practices - Technological advancements - Public perception - Incidents and controversies - Government and Industry Initiatives
How is the global trust in terms of waste-to-energy incinerators?	"The level of trust in WtE incinerators vary globally and is influenced by a combination of factors, including the track record of WtE facilities, environmental regulations, community engagement, and public perception." "Trust in WtE incinerators is dynamic and can change over time based on facility performance, community engagement efforts, and changes in technology and regulations. Building and maintaining trust is an ongoing process that requires transparency, accountability, and responsiveness to community concerns. Efforts to address environmental and health impacts	- Trust in regulatory oversight - Environmental Performance - Transparency and Accountability - Community Engagement - Public Perception - History and Reputation - Comparative Trust depending on

(*continued on next page*)

Table C.1 (*continued*)

Query	Response	Key points to consider
	while maximizing the benefits of energy recovery and waste reduction are key to fostering trust in WtE incinerators."	options - Government and Industry Initiatives - Education and Awareness - Transparency in Siting and Planning - Health and Safety Assurance
How is the global perception in terms of waste-to-energy incinerators?	"The global perception of WtE incinerators is diverse and can vary significantly depending on a range of factors, including geographical location, cultural attitudes, technological advancements, regulatory frameworks, and public awareness." "Global perceptions of WtE incinerators are not uniform, and opinions can change over time as technology improves, regulations evolve, and public awareness grows. Effective community engagement, transparent communication, and careful consideration of local concerns are critical for managing perceptions and addressing the challenges associated with WtE incineration."	- Waste Reduction (+) - Energy Generation (+) - Resource Recovery (+) - Land Use (+) - Environmental Concerns (−) - Health Concerns (−) - Odor and Aesthetics (−) - Resource Competition (−) - Waste Hierarchy (−) - Technological advances - Regulatory Environment - Cultural and Regional Differences - Media and Advocacy - Public Education
What is the global sentiment in terms of waste-to-energy incinerators?	"Determining the global sentiment in terms of WtE incinerators is challenging, as it involves a wide range of opinions and attitudes held by individuals, communities, and governments worldwide. Sentiment can vary greatly depending on factors such as location, environmental regulations, technological advancements, and public awareness efforts." "Sentiment is dynamic and context-dependent. Public awareness, education, community engagement, and facility performance all play a role in shaping sentiment. While some regions may have a prevailing positive or negative sentiment, within those regions, there can still be significant variations in opinion. Additionally, as technology and regulations continue to evolve, global sentiment may shift over time." "Global sentiment toward WtE incinerators tends to be mixed, with a wide range of opinions held by communities, individuals, and governments."	-Supportive Regions and Communities (+) - Environmental Benefits (+) - Mixed Opinions (Neutral) - Pragmatic View (Neutral) - Environmental Concerns (−) - Preference for Alternatives (−) - Technological Advancements - Government and Industry Influence - Media and Public Awareness

Appendix D

Table D.1
AI Tool-based indication of WtE Incinerator-related sentiment, acceptance, reputation, trust, and perception.

Country	Sentiment/ (Scale 0-100)	Overview	Acceptance/ (Scale 0-100)	Reputation/ (Scale 0-100)	Trust/ (Scale 0-100)	Perception/ (Scale 0-100)
Austria	Negative (30)	Less favored	Some acceptance (50)	Generally positive (70)	Moderate to High (70)	Generally positive (70)
Belgium	Mixed (45)	Used/ potential opposition	Accepted (45)	Mixed (50)	Moderate (45)	Mixed (50)
Croatia	Mixed (45)	Variation	Varies (45)	Mixed (45)	Moderate (45)	Mixed (45)
Czech Republic	Mixed (45)	One of the methods/ environmental concerns	Accepted (50)	Mixed (45)	Moderate (45)	Mixed (45)
Denmark	Positive (70)	Positive view/ significant role in waste management	High Acceptance (70)	Generally positive (75)	High (75)	Generally positive (75)
Estonia	Mixed (40)	Part of waste management/ debates about environmental impact	Some acceptance (40)	Mixed (45)	Moderate (40)	Mixed (45)
Finland	Positive (70)	Supported as a part of waste management strategy	Accepted (60)	Generally positive (70)	High (75)	Generally positive (70)
France	Mixed (45)	Used/ potential opposition/ environmental and health concerns	Varies (45)	Mixed (50)	Mixed (50)	Mixed (50)
Germany	Mixed (50)	Used/ waste reduction and recycling favored	Varies (50)	Generally positive (70)	High (75)	Generally positive (70)
Greece	Neutral (50)	Environmental concerns/ opposition	Varies (40)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Hungary	Mixed (45)	Part of waste management system/ potential opposition/ environmental concerns	Varies (45)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Iceland	Neutral (50)	Focus on other methods	Varies (30)	Generally positive (60)	Moderate (60)	Generally positive (60)

(*continued on next page*)

Table D.1 (*continued*)

Country	Sentiment/ (Scale 0-100)	Overview	Acceptance/ (Scale 0-100)	Reputation/ (Scale 0-100)	Trust/ (Scale 0-100)	Perception/ (Scale 0-100)
Ireland	Mixed (45)	Used/ opposition/ emission concerns	Varies (45)	Mixed (50)	Moderate (45)	Mixed (50)
Italy	Mixed (45)	Controversial/ environmental and health concerns	Varies (40)	Mixed (50)	Moderate (50)	Mixed (50)
Latvia	Neutral (50)	Environmental concerns/ opposition	Varies (30)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Lithuania	Mixed (45)	Part of waste management system/ opposition/ environmental concerns	Varies (40)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Luxembourg	Neutral (50)	Environmental and health concerns	Low acceptance (30)	Generally negative (30)	Low (30)	Generally negative (30)
Malta	Neutral (50)	Environmental concerns	Varies (30)	Generally negative (30)	Low (30)	Generally negative (30)
Netherlands	Positive (70)	Generally accepted as a part of the waste management system	Accepted (60)	Mixed (50)	Moderate (45)	Mixed (50)
Norway	Positive (70)	Positive view/ part of waste management strategy	High Acceptance (70)	Generally positive (75)	High (75)	Generally positive (75)
Poland	Mixed (45)	Used / opposition/ environmental concerns	Varies (45)	Mixed (45)	Low to Moderate (35)	Mixed (45)
Portugal	Neutral (50)	Environmental concerns	Varies (30)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Romania	Mixed (45)	Used / Opposition/ environmental concerns	Varies (45)	Mixed (45)	Low to Moderate (35)	Mixed (45)
Slovakia	Mixed (45)	Used / opposition/ environmental concerns	Varies (45)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Slovenia	Mixed (45)	Part of waste management system / opposition/ environmental concerns	Varies (45)	Mixed (45)	Low to Moderate (40)	Mixed (45)
Spain	Mixed (45)	Used / opposition/ environmental concerns	Varies (45)	Mixed (50)	Moderate (45)	Mixed (50)
Sweden	Positive (70)	Positive view/ part of waste management strategy	High Acceptance (70)	Generally positive (75)	High (75)	Generally positive (75)
Switzerland	Positive	General acceptance as a part of the waste management system	Accepted (60)	Generally positive (70)	High (75)	Generally positive (70)
Ukraine	Neutral	Environmental concerns	Varies (30)	Mixed (45)	Low to Moderate (35)	Mixed (45)
United Kingdom	Mixed	Used / Opposition/ environmental concerns	Varies (45)	Mixed (50)	Moderate (45)	Mixed (50)

Appendix E

Table E.1
Selected media hits – what do they measure.

Source	Date	Headline	Main content	Sentiment reviewed (machine)	Correct sentiment	Measures product reputation	Numerical value (1-5)	Summary
Wimbledon Guardian	17/05/2021 00:40:44	Merton TV proves recycling is being incinerated in Beddington	Recycled waste is being incinerated	negative	yes	no	-	The negative hit is correct and measures the customer
Find a Tender	13/05/2021 23:29:39	Pre-Market Engagement for Healthcare Waste	Tender announcement	positive	yes	no	-	The positive hit is correct and relates to a tender announcement
Letsrecycle.com	10/05/2021 17:51:27	Veolia with Suez: a global and UK ambition	Company-generated/ incinerator deals	positive	yes	no	-	The positive hit is correct and is related to corporate reputation

(continued on next page)

Table E.1 (*continued*)

Source	Date	Headline	Main content	Sentiment reviewed (machine)	Correct sentiment	Measures product reputation	Numerical value (1-5)	Summary
What do they know (PDF)	30/04/2021 17:37:37	Financial information relating to the North London Heat and Power Project (NLHPP) / Edmonton Incinerator	Financial information related to a WtE project	positive	yes	no	-	The positive hit is correct and relates to project financial info (another issue)
Dorset Echo	29/04/2021 23:05:50	Portland waste incinerator decision date unconfirmed as further questions raised	Opposition against incinerator	negative	yes	yes	1	The negative sentiment is correct and measures negative product reputation, project risks
Bognor Regis Observer	27/04/2021 15:02:41	Revised Ford incinerator plans ‘still an unsightly monstrosity’	Revised plans due to objection/ WtE incinerator	negative	yes	yes	1	The negative sentiment measures negative reputation via risk experience and local resistance
Guardian (The)	24/04/2021 15:38:52	Green – or envious? The winners and losers in Britain’s climate change plan	Winners and losers of climate change plan	negative	yes	no	-	The negative hit is correct but measures WtE policy, not product directly
News & Star	24/04/2021 13:25:22	Cumbria County Council admits 'error' for incinerator plans at Carlisle's Kingmoor Park	Opposition towards incinerator	negative	yes	yes	2	The negative hit is correct and measures local opposition and a negative reputation
TheyWorkForYou	24/04/2021 10:24:14	Topical Questions	Opposition against incinerators: Cynon Valley Waste incinerators emit toxins and pollutants that are harmful to human health	negative	no	yes	1	The machine indicated positive sentiment is incorrect while the actual sentiment is negative. The negative sentiment measures local resistance and indicates a negative product reputation via risk experience.
Kent Online	22/04/2021 11:19:15	Allington incinerator passes half a million waste deliveries landmark	Incineration in operation passes a milestone	positive	yes	yes	4	The positive hit is correct and measures positive influence on product reputation via achieved performance milestone
Cumbria Crack	21/04/2021 00:59:15	Investigation launched after ‘administrative error’ in Carlisle incinerator application	Opposition towards incinerator, moving grate not wanted should be newer, cleaner and more efficient, citizens and city councils oppose	negative	yes	yes	2	The negative hit sentiment is correct and measures negative product reputation via risks related to technical performance
Greatest Hits Radio	14/04/2021 19:48:49	Developers submit revised plans for massive Ford incinerator	The company generated plans announcement for a massive incinerator	positive	yes	yes	4	Positive hit measures positive reputation influence by the project developers
Resource	01/04/2021 18:29:44	Global Day of Action initiative pushes for a zero-waste strategy post-COVID	Incinerators make climate change worse	negative	no	yes	1	Automatic sentiment detection is incorrect, while the hit measures negative reputation via environmental risk experience.

The calculated product reputation score from the table as a mathematical average of the Likert scale numerical values is = 2, which is low.

Data availability

The data that has been used is confidential.

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