ARTIFICIAL INTELLIGENCE IN THE ENERGY UTILITIES INDUSTRY: A MATURITY MODEL INTEGRATING ENERGY SECTOR DYNAMICS AND EU REGULATION

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Examiner: D.Sc. Tech., Tero Rantala

ABSTRACT

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Artificial Intelligence in the Energy Utilities Industry: A Maturity Model Integrating Energy Sector Dynamics and EU Regulation

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The following research introduces a holistic artificial intelligence (AI) maturity model designed to elucidate on the opportunities and challenges faced by EU energy utilities organizations in the leveraging of AI. This addresses the literature gap in AI maturity models, which simultaneously encompass European Union (EU) regulation as well as the full scope of both energy utilities use cases and non-technical opportunities for AI. The artifact was developed using a simplified design science research (DSR) methodology, combining literature synthesis with a triangulated thematic analysis of energy stakeholder interviews, public panels, and large language model (LLM) feedback to iteratively refine the model. The final model comprises the following dimensions: workflows & impact assessment, organizational & human capability, strategy & leadership, risk management & ethics, external stakeholders, data foundations, and technology & infrastructure. The results indicate that data related bottlenecks, human capability, regulatory nuances, and cybersecurity risks represent the primary challenges to AI diffusion within the sector.

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ABBREVIATIONS

AI	Artificial Intelligence
AIA	The European Union Regulation for Artificial Intelligence
AIMM	Artificial Intelligence Maturity Model
CMM	Capability Maturity Model
DERs	Distributed Energy Resources
DL	Deep Learning
DSR	Design-Science Research
ESAIMM	Energy Sector Artificial Intelligence Maturity Model
EU	European Union
GenAI	Generative Artificial Intelligence
GDPR	General Data Protection Regulation
IoT	Internet-of-Things
IT	Information Technology
LLM	Large Language Model
ML	Machine Learning
OT	Operational Technology
RAI	Responsible Artificial Intelligence
ROI	Return on Investment
SCADA	Supervisory Control and Data Acquisition
SDGs	Sustainable Development Goals (EU)

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DECLARATIONS

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AI usage

The author of the thesis, Milena Jortikka, used the following AI-tools during the preparation of the thesis:

1. Perplexity (Perplexity AI)
    a. Purpose of use: Maturity model refinement
    b. Explanation: The LLM was used a component of artifact refinement
2. ChatGPT (OpenAI)
    a. Purpose of use: Maturity model refinement
    b. Explanation: The LLM was used a component of artifact refinement
3. Microsoft Copilot (Microsoft)
    a. Purpose of use: Maturity model refinement
    b. Explanation: The LLM was used a component of artifact refinement
4. DeepSeek-V3 (DeepSeek)
    a. Purpose of use: Maturity model refinement
    b. Explanation: The LLM was used a component of artifact refinement

Responsibility

The author, Milena Jortikka, takes full responsibility for the content of this thesis and has reviewed and edited the content generated by the possible use of AI tools.

1. Introduction

Artificial intelligence (AI) has become an inescapable topic of conversation in practically every sector of the economy, impacting now more than ever, even more traditionally conservative industries such as the energy sector. An industry at the center of two crucial societal transformations – digitalization and decarbonization – where AI stands as both an enabler and beneficiary of both phenomena. Subsequently, energy organizations exist in the favorable yet challenging position of simultaneously siphoning the potential value presented by AI, while tackling an evolvingly complex and uncertain regulatory landscape, facing challenges regarding data and IT/OT integration, as well as ensuring robust cybersecurity measures given the increased vulnerability digitalization often incurs (Shahverdi et al., 2025; Sheta et al., 2026). Moreover, the energy sector stands to benefit not only from potential optimizations to standard organizational workflows but furthermore in energy industry specific use cases, such as enhanced load forecasting, stabilization of power grids, and predictive maintenance of physical assets (Abonamah et al., 2025; Heymann et al., 2023; Raihan, 2023). Within this context, AI emerges as both an enabler of efficiency and innovation as well as a source of complexity and risk for critical infrastructure organizations (Espinosa Apráez & Noorman, 2024; Heymann et al., 2023). Furthermore, considering the phenomenon of weak value-capture and return on investment (ROI) from a large portion of AI initiatives (Bloedorn et al., 2023; Challapally et al., 2025; Ozkaya et al., 2026), there exists a clear opportunity to examine what determines successful AI integration in energy utilities organizations.

1.1. Background and Motivation

It is undeniable that AI has become a decisive competitive advantage within the rapidly digitalised markets of today, with the potential to optimise operations, reduce costs, and increase overall productivity. The potential value provided by AI has reached even more risk-averse industries such as the energy sector, where AI stands to optimize predictive maintenance and energy distribution (Heymann et al., 2023; Raihan, 2023). Consequently, AI holds the potential to enhance every facet of operations, from technical systems to

strategic decision-making to day-to-day operations. Furthermore, given the essential role of energy in our society, the organizations which produce and distribute it have a far higher bar when it comes to ensuring safety and stability in their operations. Subsequently, when integrating transformative technology such as AI there exists a far higher bar of rigour required for its implementation, including mitigating risks related to ethical deployment and cybersecurity (McCormack & Bendechache, 2026). Moreover, the relationship between AI and EU regulation stands as a particularly relevant consideration given the interaction of the EU's AI Act (AIA), General Data Protection Regulation (GDPR), and the sustainable development goals (SDGs) within the sector (Andrade & Vasquez, 2024; Heymann et al., 2023).

An increasingly popularised tool for the evaluation and scaling of AI capability is that of the artificial intelligence maturity model (AIMMs), a specialised derivative of the capability maturity model (CMM). An AIMM functions as a high-level capability assessment of a firm's overall ability to take advantage of AI, considering maturity in a discrete number of key domains. However, while the concept has become more popular within recent years, with a growing number of models dedicated to specific purposes and domains being developed (Sadiq et al., 2021), there seldom exists as AIMM which holistically addresses the specific context of EU energy industry organizations, explicitly tying in regulation, industry-specific use-cases, and value driven adoption. This thesis therefore aims to address the current gap through the development of an ESAIMM.

1.2. Research Objectives and Questions

The primary aim of the present thesis is the development of an AIMM tailored to the specific needs and context of EU energy utilities organizations. The ESAIMM presented subsequently aims to assist energy organization leaders and stakeholders in the assessment of current capability, while providing a roadmap for strategic AI diffusion through outlining the key dimensions and indicators for the holistic AI utilization. Furthermore, the research conducted strives to explore the opportunities and primary bottlenecks for AI diffusion within the context of EU energy utilities organizations.

The main objectives of this thesis can therefore be summarised as follows: 1) The evaluation of the current relationship between the energy industry and artificial intelligence, 2) The development of an ESAIMM, 3) The exploration of the crucial facets for holistic AI diffusion for energy sector organization. The research questions of interest are defined as:

- RQ1: What are the key dimensions and indicators constituting a holistic artificial intelligence maturity model for EU energy sector organizations?
- RQ2: How can AI be utilized to drive value for energy firms and what challenges does the sector face in its integration?
- RQ3: Which factors distinguish energy utility organizations with advanced AI maturity from those limited to experimentation and pilot-stage implementations?

1.3. Methodology, Scope, and Delimitations

The research conducted follows a simplified design-science research (DSR) methodology as defined by Becker et al. (2009), grounded in a synthesis of existing AIMM literature and AIA requirements, with a triangulated thematic analysis of semi-structured qualitative interviews with industry stakeholders, insights from public industry panels and interviews as well as LLM-based evaluation providing feedback for model refinement. Thematic analysis was conducted using a hybrid coding approach, enabling the identification of recurring patterns across data sources. Triangulation was achieved through a comparative analysis of the themes from interviews, panel discussions, literature, and LLM-assisted feedback. Furthermore, all finding were critically evaluated against established literature to mitigate bias and ensure validity.

A DSR methodology was selected for its ability to facilitate a systematic approach to artifact development, while being grounded in both theoretical and practical perspectives. Furthermore, the precedence of DSR as a methodology in research with aligning objectives (AIMM model development) to those of this thesis, including that of research conducted by Sonntag et al. (2024) and Jantunen et al. (2021), also prompted the adopted research approach of this thesis.

The scope of the research conducted is to design, refine, and preliminarily validate an AI maturity assessment artifact tailored to the EU energy sector, grounded in existing AI

maturity and digital transformation literature. Exploration of AI maturity within the EU context therefore acts as the primary delimitation for the study, chosen due to the relevance of the EU AI Act and the anticipated role of AI in supporting EU decarbonization efforts. Furthermore, while regulation such as the NIS2 Directive and Cyber Resilience Act could act as additional components for the development of the ESAIMM, the research presented focuses on the AIA as its main regulatory framework with support from the GDPR. The decision to exclude other directives was made to manage the scope of the study and ensure the clarity and focus of the final model. In terms of organizational scope, this study does not address the challenges of small and medium-sized energy (SMEs) utilities, and thus its findings may not be representative of AI maturity in this segment.

2. Literature Review

The integration of digital technologies such as artificial intelligence into the energy utilities sector has acted as a prominent facilitator in the enhancement of operations amid the global push for decarbonization and clean energy (Di Chiacchio et al., 2026; Wang et al., 2025), However, organizations continue to face a myriad of challenges in adoption, assessment, and compliance of the technology in order to drive real business value (Andersson, 2025). The aim of this chapter is to outline the background essential to the understanding of the subsequent research within this thesis, encompassing a general overview of AI, the transformative role it could play within the energy utilities industry, the role of AIMMs for organizational capability assessment, and the impact of EU regulation on energy utilities organizations. While this section will explore energy sector use cases of AI and the current status of EU regulation, there is no in-depth examination of the technical or legislative aspects of AI. The narrative literature review conducted consequently synthesizes key findings and themes to contextualize the study and inform the design, development, and evaluation of the proposed artifact later in the report. As such it does not function as a deep systematic evaluation of the literature and its methods but rather serves as a foundational overview of the necessary context for model development.

2.1. Artificial Intelligence, the Energy Sector, and Sustainability

The interplay between AI and the energy industry is one that has served as a key impetus in the burst of innovation addressing transformation into a more circular, decarbonized, and sustainable society (Abonamah et al., 2025). This section therefore aims to elucidate on the evolution and simultaneous interplay of AI and the energy industry, and their combined role in global decarbonization efforts.

2.1.1. Overview of Artificial Intelligence

Artificial intelligence use has only continuously grown within recent years with a record high of 88% of organizations reporting to using the technology in a minimum of one business function in 2025 (Singla et al., 2025). However, while the term may be rapidly increasing in popularity, there exists a lack of consensus when it comes to what it precisely refers to and its specific boundaries (World Bank Group, 2025). Fundamentally, AI can be understood as a broad umbrella term for systems that process data to perform tasks typically associated with requiring intelligence to accomplish, including reasoning, learning, and perception (Alawamleh et al., 2024). AI as an algorithm is subsequently highly dependent on the data it interacts with and trains on. Consequently, it exists in close practical usage with other data-centric technologies such as Internet-of-Things (IoT) devices (Li et al., 2023).

AI has evolved to encompass a myriad of subsets since its coining in the 1950's, including that of machine learning (ML) and deep learning (DL). Although existing as a concept for decades, the field was significantly invigorated in the late 20th century by the development of ML, which enabled the transformation from the first rigid, rule-based AI systems to the flexible, data-driven methods seen today (Rahman & Mehnaz, 2024). To further elaborate, ML can be understood as a subset of AI that enables systems to learn from data to identify patterns, make predictions, or automate tasks, often improving performance over time and requiring human oversight for data curation and validation. It is therefore typically utilized to manage and extract valuable information and patterns from large pools of data (Antonopoulos et al., 2020). A further subset of AI is that of DL, which differs from ML in its lack of need for human labelled data and its ability to handle and process higher levels of abstraction (IBM Data and AI Team, 2023).

Evolving from simple rule-based systems, current integration and innovation relating to AI is primarily interested in the potential value presented by ML and DL. Especially that of DL, which forms the backbone for generative artificial intelligence (GenAI) and agentic AI due to the ability to not only process vast amounts of data but adapt to changing needs and environments and perform at higher levels of abstraction (IEA, 2025). While the utility of ML and DL have been showcased in a number of studies, there remains many uncertainties, including their black-box nature and explainability (Antonopoulos et al., 2020), reliability

(Henao et al., 2025) as well as risks in terms of the perpetuation of human bias (Shobanke et al., 2025).

Beyond the core three domains a multitude of variations and subsets have developed. Perhaps causing the most excitement being that of generative AI (GenAI) and Agentic AI, which have seen broad implementation and investment within recent years. GenAI stands out in the fact that it is able to not only process existing data to complete task such as predictive modelling or data analysis but has the capability to create new material utilizing DL and advances in large language models (LLMs). Agentic AI on the other hand are autonomous systems that can execute multiple step goals and therefore have the potential to take on complex multidimensional tasks without necessitating human oversight (IEA, 2025; World Bank Group, 2025).

It is undeniable that the landscape of AI is one that is evolving at an unseen rate and therefore can be expected to simultaneously foster innovation and as well as new challenges. The widespread introduction of AI to the public has functioned much like Pandora's box, unleashing a torrent of transformative potential for stakeholders across industries to optimize resource allocation, streamline operations, and dramatically enhance productivity. Yet at the same time, it has released profound challenges, including the technology's voracious appetite for vast datasets and immense computational energy, labour market disruptions fuelling widespread fears of job displacement, escalating cybersecurity vulnerabilities, as well as ethical dilemmas around bias and privacy (Rahman & Mehnaz, 2024). As such, it is essential to ensure that it is adopted in a manner that supports its positive transformative potential while mitigating the associated risks (Alon et al., 2025).

2.1.2. Artificial Intelligence within the Energy Industry

AI has become a widely pervasive technology in practically every industry present world-wide including the energy sector, where it possesses the potential to assist with both industry specific functions as well as general business operations (Heymann et al., 2023). Energy specific use cases of AI include functions such as grid stabilization, forecasting of energy production and consumption (Henao et al., 2025), facilitation of energy storage and distribution innovation (Wang et al., 2025), renewable energy technology integration, power

production & consumption optimization, advanced predictive maintenance, and so much more (Di Chiacchio et al., 2026). As for concrete metrics, it has been found to optimize the management of complex electricity networks, reducing downtime by up to 30-50% (IEA, 2025), improving harmful emissions by up to 20% (Uriarte-Gallastegi et al., 2024), improving grid efficiency by 15% with 10-20% enhanced battery storage capacity (Oladapo et al., 2024). Each addition serves not only to make operations more efficient, but to enhance business value, sustainability, and long-term competitiveness for energy organizations, with studies showing enhanced long term financial performance and resistance to risk in firms that adopt sustainable practices (Uriarte-Gallastegi et al., 2024). Consequently, AI has been held as a primary technological enabler in the sustainable energy transition (Zhang & Strbac, 2025), and pivotal in the meeting of sustainability directives such as the United Nations' sustainable development goals (SDGs) (Shahverdi et al., 2025)

However, while the research overall shows a great potential for AI to optimise and ultimately serve as one of the main cornerstones in the current energy transition, there remains many technical, operational, economical, and ethical challenges. On the technical end this encompasses problems ranging from integration with legacy systems to data integrity, economic problems with the high costs of infrastructure and implementation, as well as unsure ROI for AI initiatives (Andersson, 2025; Henao et al., 2025; Park, 2025). Furthermore, with increased complexity and digitalization of EU energy systems, there are many increased opportunities for cybersecurity attacks (Algburi et al., 2025; IEA, 2025). Socio-technological problems ranging from skill gaps and labour resistance to adoption, as well as issues pertaining to the systematic perpetuation of bias through algorithms additionally serve as challenges in adoption (Andersson, 2025; Park, 2025). Moreover, specifically within the EU there lies the highly relevant consideration of emerging regulation, which serves as another facet which energy utilities firms must take into account, especially considering their higher transparency and risk mitigation obligations as a sector of high criticality (Curro et al., 2025; Heymann et al., 2023). Overall, there are many barriers which must be carefully assessed and managed, especially in such a foundational industry where mishaps in terms of implementation can have severe consequences to the public. For comprehensive assessment and integration, AI initiatives must encompass the technical, economic, operational, and social facets and presented by the current landscape.

2.1.3. The Paradox of AI and Sustainability

There exists an often-paradoxical relationship between the energy sector and AI – an ouroboros of use and consumption in terms of not only energy, but additionally other critical resources such as rare earth minerals and water (IEA, 2025; Luccioni et al., 2025). As previously discussed, AI has shown great potential in facilitating better grid resilience, optimizing the production, distribution, storage, and forecasting of energy. All of which stand to improve performance and efficiency in energy utilities. However, simultaneously a vast amount of energy is necessitated for computation and training through data centres (Senyapar & Bayindir, 2025), which are only predicted to grow at a rate of up to 3% of all the world's energy consumption by 2030 (WEF, 2025). The debate of AI's role in decarbonisation and sustainable development is therefore rather contentious is nature, with only further complexity being added when examining not only direct but indirect impact (Luccioni et al., 2025).

The Jevon's paradox refers to the theory that technologies that are designed to optimize the usage of a certain resource often end up fuelling increased adoption of said technology and therefore ultimately cause a total increase in the consumption of the original intended resource. On the point of AI, this speaks to the potential rebound effect that comes with gains in energy efficiency (Luccioni et al., 2025). This aspect of AI is one that is often lacking in current industry discourse and could be detrimental to decarbonization efforts, with exponential demand leading to a forced returned dependence on fossil fuels in order to keep up with demand (IEA, 2025; Lal & You, 2025). However, the extent of this rebound is still in debate, and may remain so due to the multifactorial and nuanced relationship of AI and energy. The framing of this challenge should consequently focus on individualised contexts, as well as detailed and nuanced understanding in order to facilitate truly productive conversation and collective development (Luccioni et al., 2025).

2.2. Maturity Models, Artificial Intelligence, and Assessment of Capability

The diffusion of AI is frequently cited as a complex undertaking, as it demands transdisciplinary expertise to address the full range of requirements related to its evaluation

and integration. This difficulty being echoed in recent reports, indicating difficulty by a majority of organisations to realize the potential benefits of AI in their processes (Hansen et al., 2024). Maturity models have long held as a tool through which organizations can identify and target their weaknesses in terms of reaching their desired state, benchmarking against competitors, assessing capabilities, and overall assisting with aligned organizational development. Maturity becoming a popular means of assessing capability since the introduction of the capability maturity model (CCM) in the 1990's. A structured AI maturity assessment is vital, providing organizations with targeted dimensions for gap analysis, goal-setting, and progress measurement, which without, advancements remain unguided (Saari et al., 2019; Sadiq et al., 2021; Sprengel & Ulrich, 2025). The following sections will hence cover AIMMs both conceptually and synthesize current trends and characteristics within the literature.

2.2.1. Overview of Artificial Intelligence Maturity Models (AIMMs)

At their core AIMMs are artifacts through which firms can assess their own level of readiness in terms of leveraging artificial intelligence within operations. Furthermore, they can be used to support in benchmarking against other firms as well as serve as a roadmap for future AI development (Saari et al., 2019; Sadiq et al., 2021). Moreover, while often based on traditional maturity models focused areas such process improvement, AI specific maturity models are needed to address the specific and unique requirements of AI systems (Muñoz-Ordóñez et al., 2025) Therefore, AIMMs can function both as a descriptive, prescriptive, and comparative tool for organizations to ensure structure and specificity in AI maturity assessment and targeted development. Overall, assisting with alignment of goals as well as scaling from ad-hoc, manual processes to data-driven, strategic, and automated AI implementations to improve performance and competitiveness (Kubilay and Celiktas, 2025; Saari et al., 2019; Sadiq et al., 2021).

The qualities of AIMMs can vary quite a bit in focus, dimensions, attributes, purpose, and scope. However, there are many conventions in design and content which can be seen repeated throughout different models. One common characteristic being that of the maturity scale, with most ranging from 3-6 beginning from initial and ending optimised practices. Moreover, the main dimensions typically included are that of strategy, technology, data,

people, and governance, with a systematic literature review (SLR) by Sadiq et al., finding the key dimensions for assessment to be that of data, analytics, technology and tools, intelligent automation, governance, people, and organization (2021), while culture & competencies, strategy, data, organization & processes, and technology were highlighted by Sonntag et al. (2024).

Since their introduction, beginning from the Software Engineering Institute's launching of the CMM in the early 1990's, the pool of maturity models has only increased and diversified in form as well as purpose (Vakkuri et al., 2021; Saari et al., 2019). This includes specialization on ranging industries as manufacturing (Sonntag et al., 2024), the all the way to healthcare (Hussein et al., 2026). Furthermore, the specific purpose of AIMMs has also diversified, with different models addressing specific areas within AI governance (Sadiq et al., 2021). This includes its intersection with domains such as the responsible and ethical diffusion of AI, with journal articles such as those by Jantunen et al., (2021), McCormack & Bendechach (2026), and Vakkuri et al (2021). Moreover, most studies within the field also emphasize creating new AI maturity models, often for specific industries or purposes, which can be valuable in ensuring a comprehensiveness for that specific domain/purpose which generic models may not be ankle to produce (Sadiq et al., 2021).

The construction of maturity models typically involves either a top-down approach or a bottom-up approach, where a top-down approach involves the formation of distinct levels of maturity and then after defines the criteria and characteristics that must met to meet each level of maturity. Contrastingly, the bottom-up approach defines model characteristics first and then levels of maturity afterwards, which as a method is the more popular approach in AIMM design. Furthermore, validation and evaluation of AIMMs is often lacking in much of the research. However, when conducted often is done using a design-science research methodology with delpi studies, qualitative interviews, or forms uses for model evaluation (Akbarighatar et al., 2023; Kubilay and Celiktas, 2025; Sadiq et al., 2021).

While there may be more research continuously being published in the area, there is still many uncertainties and debates surrounding effectiveness, comprehensiveness, validity, and best practices in implementation. Firstly, a majority of current maturity models tend to not include or only partially consider important criteria such as cybersecurity, data protection, top-management support, and the quality of data (Sonntag et al., 2024), which can lead to incompleteness in maturity assessment. Furthermore, a systematic literature review by Sadiq

et al. (2021) found that around 46% of studies focus solely on the technological aspects of maturity assessment models. And while technology is central, it is simultaneously imperative to consider aspects such as organizational support and ethics, especially considering that previous research has shown non-technical challenges to be a significant hurdle in the integration of AI (Hansen et al., 2024). Moreover, Kubilay and Celiktas (2025) argue that most maturity models fail to take into account the interdependencies of AI, digital transformation (DT), and cybersecurity, which weakens model strength and rigour. As an example, the authors point to the Gartner AI Maturity Model with its sole focus on AI, without proper consideration of either of the other two interdependent domains, revealing the siloed approach taken in the development of many AIMMs. Furthermore, Hansen et al. (2024) points to the significance of understanding individual context and struggles rather than singularly relying on AIMMs for capability, due to the complex nature of AI as a technology and the nuanced position each organization exists within.

Overall, the research reflects a common trend of a growing focus of AIMMs on specific industries and purposes, yet a lack of consideration for certain key dimensions, especially non-technical and socio-organizational factors. Furthermore, validation in a majority of AIMMs is lacking (Kubilay and Celiktas, 2025; Sadiq et al., 2021), indicating a clear need for future research aimed to assiduously validate AIMMs through real case-study implementation. Emerging areas of consideration for strategic alignment include regulatory impact, workforce training for AI adoption, and ethical AI governance (Kubilay and Celiktas, 2025).

2.3. European AI Regulation and the Energy Sector

As AI becomes ever-increasingly embedded in societal and industrial systems, its potential benefits and risks have become a central discussion among academics and policymakers alike. Consequently, a clear understanding of the regulatory space and restrictions is vital to ensure compliant, responsible, and sustainable AI integration (Di Chiacchio et al., 2026). The main piece of legislation contributing most significantly to the regulation of AI being that of Regulation (EU) 2024/1689 also known as the AI Act (AIA), supported by other regulation such as the General Data Protection Regulation (GDPR), the Data Act, and the Cyber Resilience Act. The AIA came into force on August 1st, 2024, with full applicability

in August 2nd, 2026. The legislation is designed to act as the first-of-its-kind comprehensive legislative framework for the utilization and design of AI systems within the EU. A central aim to balance the innovation and risk potential of AI and therefore protecting consumers while enabling the proliferation of trustworthy and human-centric AI (European Commission, 2026; Graux et al., 2025; Hickman et al., 2025; Hohmann & Kollár, 2025). It aims to accomplish this through outlining risk-based rules that the developers and deployers of AI must meet for compliance, with four levels of risk and their subsequent requirements for AI systems defined. The highest set of risk, "unacceptable risk", relates to harmful AI systems which infringe upon the livelihoods and safety of people, while "minimal risk" AI systems are largely unregulated with no obligations under the AIA. On the other hand, "limited risk" AI systems require a higher level of transparency when it comes to its AI systems, with a high focus on ensuring users understand that they are interacting with an AI system such as chatbot. However, the highest level of attention within the AIA is dedicated "high level risk" AI systems (European Commission, 2026; Future of Life Institute, 2024), including AI systems within energy utilities (Heymann et al., 2023; Official Journal of European Union, 2024).

The AIA will treat most AI used by energy utilities as "high-risk" critical infrastructure systems, due to their role in supplying electricity and heating. Consequently, academics such as Heymann et al., (2023) argue that the AIA is likely to cause strong consequences for the energy utilities industry in the deployment of AI. Moreover, for AI systems that fall under the "high-risk" classification, energy utilities organizations will have to implement risk management systems throughout the systems lifecycle, establish quality management systems as well as thorough data governance pertaining to the data sets used, produce technical documentation for compliance and auditing purposes, design and implement record-keeping mechanisms, provide transparency for users, and overall design high risk systems for comprehensive human oversight, accuracy, cybersecurity, and robustness (Future of Life Institute, 2024; Official Journal of European Union, 2024).

While the AIA aligns strongly with the GDPR in terms of general principles of fairness, transparency, and accountability, the act simultaneously introduces increased complexity and labour for energy organizations. This taking the primary form of increased documentation and procedural duties which must be met to ensure alignment with new regulation (Hohmann & Kollár, 2025). Moreover, with additional documentation,

provisioning information to regulatory bodies, human oversight over AI systems, and system safety verification, organizations are also expected to incur higher costs for the management of systems (Heymann et al., 2023). Uncertainty towards the impact, clarity, and scope of the AIA, have been raised by multiple authors such as Graux et al., (2025) who argue that there remains a level of ambiguity when it comes to the clarity of the terminology, classifications, and language within the AIA. This including the definition of AI as well as “high-risk "systems, which due to subjective and ambiguous language may cause issues relating, in the case of AI, to differentiation from traditional digital tools. Therefore, there exists a certain level of uncertainty when it comes to compliance, which may cause issues for many organizations especially those with “high risk” AI system classification.

Overall, the AI act and its supporting regulations will most likely increase compliance and governance obligations but also facilitate safer, more transparent and trusted AI-based operations for critical infrastructure. An impact which will not affect the EU but cause a domino effect throughout the globe in terms of regulation on AI. Energy sector organizations must therefore be prepared to invest into alignment with regulation and evaluate rigorously the AI systems which are integrated into operations (Heymann et al., 2023; Hohmann and Kollár, 2025). Furthermore, with the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) currently developing international standards for environmental sustainability in AI, there is likely to continue to be changes within the regulatory landscape (Hickman et al., 2025).

3. Methodology

The approach for artifact development follows a simplified DSR methodology as defined by Becker et al. (2009) and visualised in Figure 1. A DSR methodology was chosen due to its precedence as a systematic process for the creation of artifacts such as maturity models and its blend of both practical and literature-based rigour. Furthermore, the utilization of DSR in previous studies with similar objectives (e.g., Banh, 2025; Jantunen et al., 2021; Sonntag et al., 2024) highlight the suitability of DSR for AIMM development.

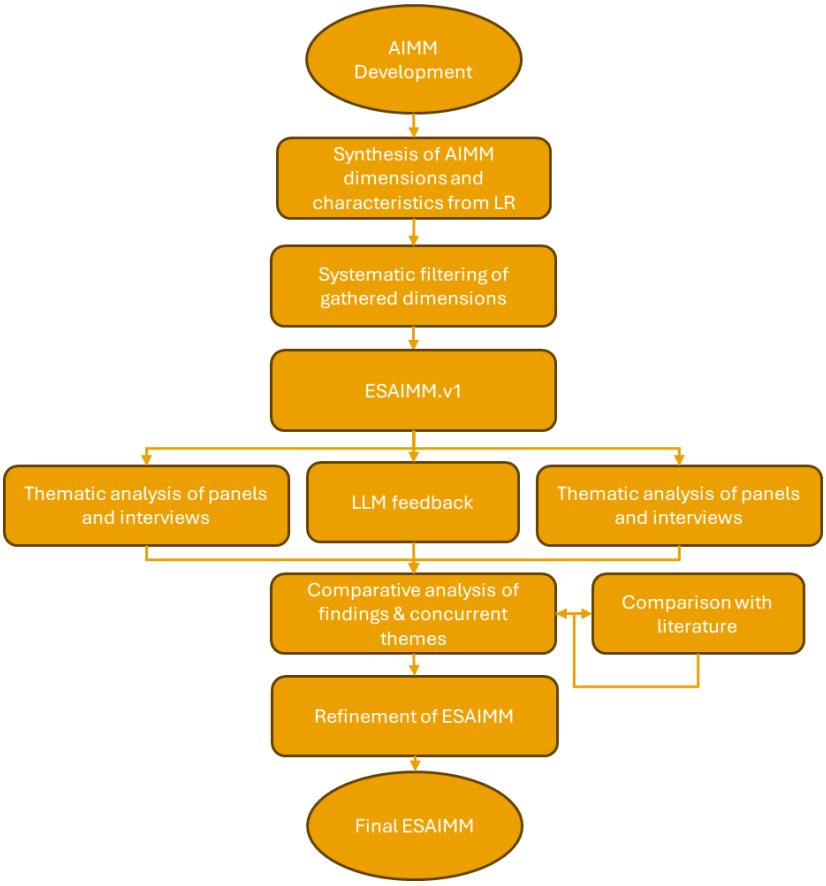

Figure 1. Methodology flowchart

The final methodology followed consists of the following stages: (1) Problem definition (e.g., defining need, scope, objectives, and target audience), (2) Analysis and comparison of existing maturity models (e.g., extracting metrics, structures, dimensions etc.), (3) Maturity model refinement and evaluation, (5) Discussion of findings.

3.1. Problem Definition

The impetus for the development of the artifact in this thesis is the need to address a gap in existing AI maturity models (AIMMs), particularly their limited consideration of the specific contexts and requirements of EU energy organizations. This includes the integration of AI capabilities across both general and industry-specific functions, as well as alignment with EU regulatory frameworks. Furthermore, given the interdisciplinary nature of AI adoption in energy utilities, the proposed artifact aims to synthesize key dimensions of AI diffusion, including responsible AI (RAI), regulatory compliance (e.g., the EU AI Act), and sustainability considerations (e.g., SDGs). The objective of the model is therefore to assist energy organizations and professionals in both the assessment of current AI capability and the facilitation of value-driven AI adoption.

Maturity within the given framework is not defined simply by the extent of AI embedding into company processes and strategy but includes the extent to which value capture is occurring due to its integration. This hopes to address the phenomenon of sporadic value capture and financial returns from AI adoption by a large portion of organisations (Bloedorn et al., 2023; Challapally et al., 2025; Ozkaya et al., 2026), which is especially crucial given that most organizations within the energy sector are in their piloting or experimentation phases with scaling ahead (Singla et al., 2025). Moreover, given the energy industries comparatively lower utilization of AI (Challapally et al., 2025), a ESAIMM would be highly beneficial in ensuring a clear and comprehensive roadmap for deployment.

3.2. Synthesis and Analysis of Existing AIMMs

To begin model development, a synthesis of relevant academic and industry sources within the domains of energy utilities, AI, AIMMs, and EU Regulation was conducted. Information searching was done primary using Google scholar, Elsevier (ScienceDirect, Scopus), Semantic scholar, and Taylor & Francis for journal articles, while Google was predominantly used for industry whitepapers and legislative sources. The purpose of the chosen approach was to gather a broad view of material and perspectives on the topic. Key words during the information searching process included: “Artificial Intelligence Maturity

Model", "AI Deployment Capability", ""AI Policy & Governance", "Artificial Intelligence Maturity Assessment". Given the rapidly developing landscape of AI, publications before 2019 were not considered, with sources exclusively focused on non-European contexts also being excluded. The inclusion and exclusion criteria are outlined further in Table 1.

Table 1. Inclusion & Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
- English language publications - Published between 2019-2026 - Peer-reviewed journal articles, conference papers, PhD/Master theses, authoritative reports from EU bodies, regulators, large industry associations or major consultancies	- Non-English publications - Published before 2019 - Studies focused exclusively on non-European contexts where regulatory/market conditions are very different and not generalised to Europe - Blog posts, short press-releases

From this research pool, sources focused specifically on AIMMs (either their development or analysis) were gathered and further narrowed down to those with relevance to the energy sector. This meant discarding AIMMs specifically focused on vastly different industries (healthcare, education, etc.) or with purposes misaligned with the objective of the given research. The final pool of 20 sources was then inputted into an Excel file (Appendix 1.), outlining key metrics, extracting maturity dimensions, number of dimensions, focus/purpose, and typologies. Four inclusion criteria were used to filter the found dimensions of maturity, including:

1. Relevance to energy sector
2. Support with inclusion in a minimum of two sources
3. EU regulatory alignment
4. Expressible as an observable practices or state that stakeholders can reasonably rate in an assessment

Candidate qualities that did not meet each of the former criteria were discarded or merged into broader dimensions. The preliminary dimensions and sub-dimensions were

subsequently grouped, which facilitated the development of the first iteration of the ESAIMM (ESAIMM.v1).

3.3. Refinement of ESAIMM

Following the development of ESAIMM.v1, a structured refinement strategy was implemented using thematic analysis and triangulation. This process incorporated seven public panel discussions/interviews as well as two semi-structured interviews, alongside feedback generated by four LLMs. Findings were additionally compared and evaluated alongside the literature to ensure reliability. This refinement approach was selected for its accessibility and its ability to target specific weaknesses identified in the initial model iteration. As ESAIMM.v1 was primarily grounded in general AIMM literature, within which energy-specific models remain limited, there was a significant risk that industry-specific nuances were not fully captured. To address this, thematic analysis of stakeholder perspectives and LLM-generated feedback was conducted to develop a more nuanced understanding of the sector. The thematic analysis utilised follows the steps outlined by Ahmed et al. (2025), including; (1) familiarization with the data, (2) identifying initial codes, (3) finding collective themes, (4) evaluation of themes, (5) finalization of themes, and (6) synthesis of findings and presentation of narrative. After synthesis, each potential addition or removal to the model was cross-referenced with the literature. This was done in order to ensure the robustness and accuracy of thematic findings.

For thematic analysis, seven publicly published panels/interviews by relevant stakeholders discussing AI within energy utilities were leveraged for capturing a broad spectrum of opinions and prevalent themes. Materials included in this analysis are those by Siemens (2026), Baker Hughes (2026), Deloitte (2025), EM-Power Europe (2025), EUSEW (2024), Tom Raftery: Sustainability & Climate Talks (2024), and Databricks (2025). The given materials were chosen due to their credibility and accessibility. For video formatted sources, transcripts were extracted for coding purposes. The coding approach used was hybrid in nature, incorporating both inductive and deductive coding to ensure a comprehensive analysis. LLM-based refinement acted alongside this thematic analysis as a synthetic group of expert views in order to test for the artifacts coherence and completeness as well as identify gaps in the literature trends addressed. The process involved prompting four

different LLMs including Copilot, Perplexity, DeepSeek-V3, and ChatGPT with the prompt: "When evaluating accuracy and completeness of an AI maturity model for the energy sector based on the most recent literature and expert views, what would be the feedback towards the following model?" Each response was then documented for comparative analysis. Two 30-minute semi-structured interviews with stakeholders of an energy utilities firm, the questions of which can be found in Appendix 3, were additionally conducted.

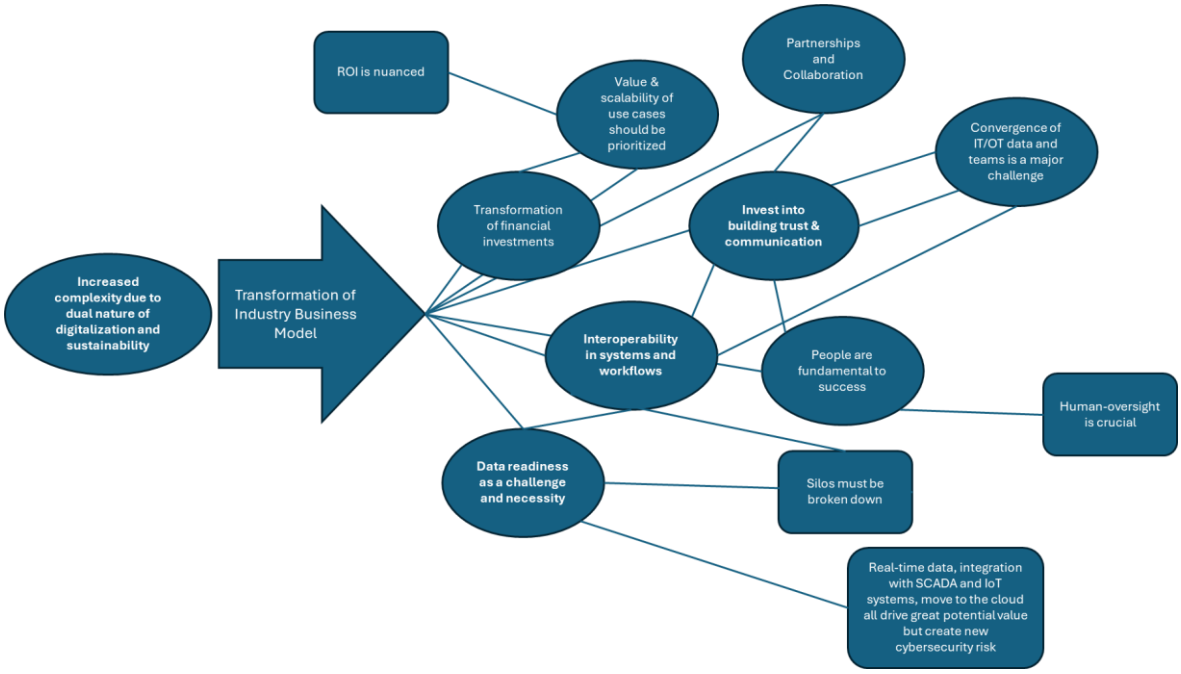

Figure 2. Thematic mapping of qualitative themes

With all material gathered and the coding process conducted, convergent themes were iteratively extracted and refined. The final mapping of the convergent themes (outlined in Figure 2), acted in the refinement process to either reinforce, weaken, or add new nuances to the AIMM. Furthermore, these themes were additionally cross-referenced with literature to ensure findings were robust and based in evidence. The comparison of themes and their discrepancies was essential for identifying key points of weakness for the model, with human oversight and categorization regarding analysis and grouping of themes being key to the AIMM refinement process followed. After the development of the high-level ESAIMM, a refined tabular iteration was developed based on the maturity levels described in Figure 3.

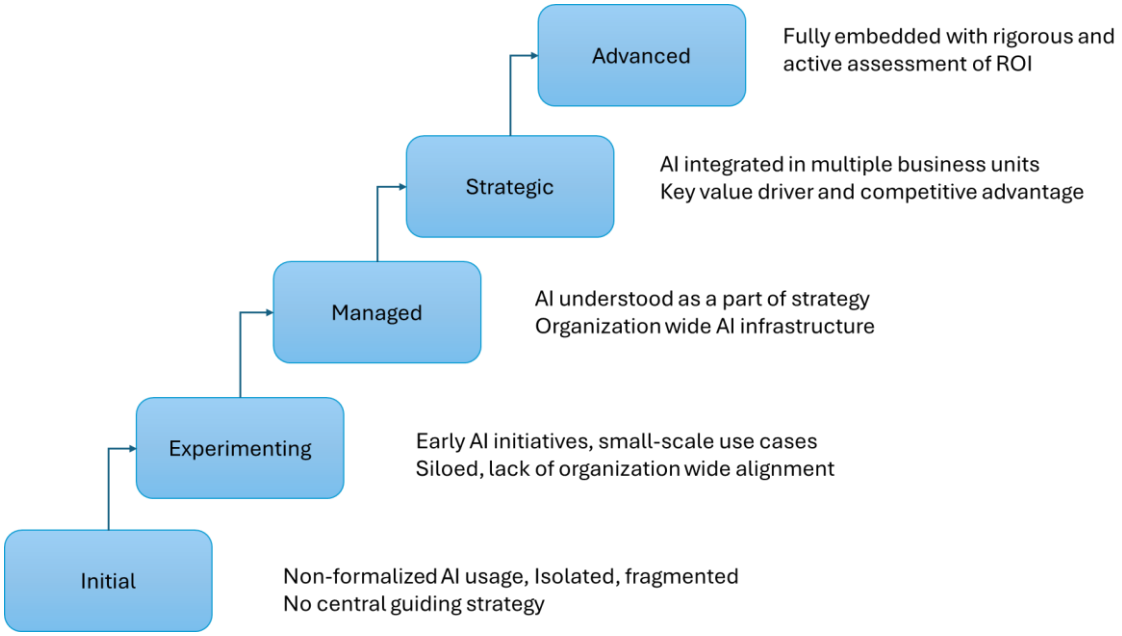

Figure 3. ESAIMM Maturity Levels

This process acted as the final step of granulation of the ESAIMM, with the objective to provide energy organization stakeholders with clear stages of maturity in each high-level dimension.

4. Energy Sector Artificial Intelligence Maturity Model

The final AIMM developed illustrated in Figure 4. contains the seven high-level dimensions of Workflows & Impact Assessment, Organizational & Human Capability, Strategy & Leadership, Risk Management & Ethics, External Stakeholders, Data Foundations, and Technology & Infrastructure. These dimensions are further encompassed by the three broader categories of Internal Capabilities, Alignment Dimensions, and Technical Capabilities. The internal capabilities dimension describes the internal and non-technical dimensions of AI maturity, while the technical dimension encompasses both physical and digital technical readiness. Contrastingly, alignment dimensions differ from the former due to their direct necessity for connection to the external environment of the organization.

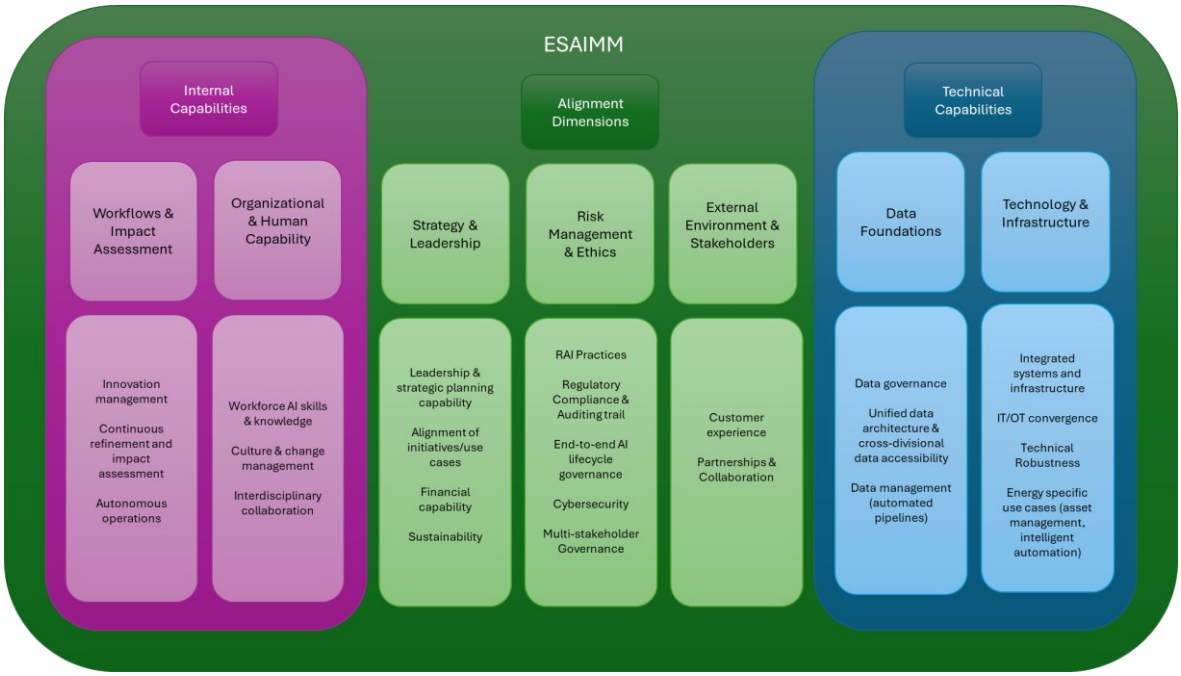

Figure 4. High-level ESAIMM Dimensions

As illustrated in Figure 4, the internal and technical dimensions of the ESAIMM constitute the core of the artifact, reflecting their foundational role in enabling AI adoption. This reflects the evidence from both the literature and industry stakeholders, which indicate that without sufficient organizational and technical capabilities, AI initiatives are unlikely to succeed.

The indicators of the ESAIMM, which further refine the dimensions of AI maturity, are outlined in detail in Table 2, 3, and 4. This is to enable easier assessment of current and evolving AI capability.

Table 2. Alignment indicators

Dimension	Strategy	Risk Management & Ethics	External Environment & Stakeholders
Initial	Minimal strategic alignment, high impact, and scalable AI initiatives Lacking support by senior management Minimal and uncoordinated investment into AI Potential AI experimentation, but lack of formal AI initiatives/pilot projects or leadership Minimal oversight of ESG, responsibilities, and policies	Reactive cybersecurity measures, poor understanding of AI specific risks (especially in relation to legacy systems) Minimal compliance documentation, limited records and weak evidence of decisions or model changes Sporadic and non-formal RAI practices (Ethics, fairness, explainability, and human oversight are not systematically addressed) No life-cycle governance AI decisons made by a narrow technical team with minimal to no input from other stakeholders	Lack of user-centric AI initiatives/enhancement of user experience No existing collaborative partnerships
Experimenting	Non-formalised/inconsistent AI leadership	Basic risk management for cyber threats and supply disruptions	Minimal enhancement of customer experience

	Evident support of AI initiatives (financial, leadership), however uncoordinated in nature Inconsistent strategic alignment of AI initiatives with organisation strategy Sustainability is considered mainly through compliance or reporting needs with little lifecycle thinking	Basic compliance documentation, but incomplete or inconsistent in nature Formalized RAI practices, but inconsistently practiced throughout organization Minimal life-cycle governance AI decisions made by technical team with basic but inactive input from other stakeholders	Weak and/or inactive collaborative relationships
Managed	Formalized AI leaders and sufficient support from senior management Clear and targeted financial investment via dedicated budget AI projects aligned with broader organization strategy and scalable in nature Sustainability requirements and strategic considerations are built into AI project selection and governance	Standardized privacy and risk management measures, including AI specific risks and legacy system integration Complete and formal compliance controls and audit trails Formalised RAI practices with human oversight and accountability practiced throughout the organization Governance spans most lifecycle stages AI decisions made by technical team and/or leadership with active input from other stakeholders	Small AI initiatives to enhance customer experience Established partner networks

Strategic	Key strategic capability with active participation from senior management Formalized and high competency AI leadership (senior AI leader/AI council) Investment tied to ROI (financial gains, efficiency gains etc.) with dedicated budget for different use cases. AI use cases are high-impact and scalable Sustainability is actively managed across AI use cases and operational workflows	Automated cyber security processes throughout all environments Compliance monitoring is routine and thorough Comprehensive RAI practices with human oversight and accountability for all AI systems Governance includes coordinated and active input of each stakeholder group within the organization, including even customer input	Multiple AI initiatives to enhance customer experience Collaborative networks with regulators, technology providers, suppliers, and partners
Advanced	Transforming strategy and vision with continuously evolving roadmap Highly capable and active AI leadership AI investments tied into core financial planning, with dynamic ROI models Sustainability is a core to strategy and embedded into architecture, procurement, and operations. ESG and other sustainability metrics continuously used in feedback refinement loops.	Real-time, AI-orchestrated risk mitigation with active monitoring of digital and physical assets Full RAI maturity with continuous improvement loops Comprehensive human oversight and accountability with embedded oversight boards and regular audits Lifecycle governance is continuously refined Forward-looking approach to	Transformational and personalised customer experience enhancement Active collaboration and innovation with regulators, technology providers, suppliers, universities, and industry partners

		regulatory changes, compliance assurance, and sustainability reporting	

Table 3. Internal capability indicators

Dimension	Organizational & Human Capability	Internal workflows & Impact Assessment
Initial	Limited AI workforce skills and knowledge Non-formal change management established No investment into training AI capability Interdisciplinary collaboration is minimal or non-existent	Innovation is opportunistic and isolated Sporadic AI innovation without structured processes for scaling, funding etc. Impact is assumed rather than measured Workflows are manual with no or isolated AI usage
Experimenting	Inconsistent AI capability and application Formalized but inconsistent and/or incomplete change management practices Minimal investment into AI workforce capability and understanding Passive and sporadic interdisciplinary collaboration	Non-centralised monitoring and subsequent refining of impact Inconsistent innovation practices and initiatives AI can automate simple tasks, but human intervention is needed in most use cases
Managed	Impactful workforce AI skill and knowledge as seen reflected in AI initiatives Formal change management and internal accountability processes defined Organization wide investment into AI capability development	Defined monitoring and evaluation processes Standardized AI innovation pipelines integrated into R&D workflows Automation is used in selected operational areas

	Active communication and collaboration between different organizational teams (especially IT/OT)	such as forecasting and maintenance scheduling
Strategic	Highly knowledgeable and skilled workforce with active participation in high impact AI initiatives Thorough change management strategy and practices established Continuous investment into AI human capital Coordinated and active collaboration between different stakeholders	Metrics like model accuracy and ROI systematically tracked Innovation is continuous and enterprise-wide Automated lifecycle tools for continuous monitoring, drift detection, and optimization
Advanced	Highly knowledgeable and skilled workforce (specialised teams and general workforce) with aligned understanding of long-term development and active development of innovative AI projects Comprehensive and continuous change management established Continuous investment, monitoring, and development of AI human capital and capability development Interdisciplinary collaboration is embedded into workflows and fuels innovation	Cross- organizational innovation ecosystems and transformational AI initiatives (business model, strategy etc.,) Impact assessment in continuous and automated where seen beneficial

Table 4. Technical capability indicators

Dimension	Data Foundations	Technology & Infrastructure
Initial	Data quality is inconsistent and siloed across OT/IT systems Manual extraction of data from sensors or spreadsheets Data handled reactively and siloed throughout organization	Siloed IT/OT tools Limited or no cloud Frequent downtime Legacy systems dominate, and infrastructure is not designed for AI workloads or secure data movement

Experimenting	Basic quality checks and lineage tracking applied Basic data pipelines for key sources like meter readings and predictive maintenance logs	Basic OT/IT architecture through IoT, sensors with SCADA systems Some cloud, edge, or analytics tools are available, but architecture is inconsistent across OT and IT
Managed	Centralized data management platform, Automated validation and master data management Data quality is consistent Automated validation and lineage tracking (supports ESG data for regulatory reporting)	Enterprise-wide platforms integrating OT sensors with AI analytics Standardized resilience Standardized digital twins for assets, intelligent automation for grid ops
Strategic	Real-time data lakes with AI-driven anomaly detection and predictive monitoring Platforms optimized for scalability	Real-time data fabrics linking assets, grid, and supply chain with AI orchestration IT/OT infrastructure is scalable, monitored, and resilient
Advanced	Self-managing data ecosystems Full interoperability across valuechains (e.g., digital twins linking supply chain to grid ops) Data fuels generative AI at scale, with continuous optimization and feedback loops	Proactive resilience using foundational digital infrastructure (digital twins, IoT, cloud computing etc.,) Intelligent assets (e.g., self-optimizing grids, AI-orchestrated renewables/DERs)

5. Discussion of Results

The aim of the research conducted was the development of an AIMM specifically tailored for EU energy utilities organizations. This aim was accomplished utilizing both academic and industry sources through simplified DSR methodology, with a synthesis of existing AIMMs and refinement through a comparative thematic analysis of public panels and interviews by relevant stakeholders, LLM feedback, and two thematic interviews with energy stakeholders from a utilities company in Finland. The following discussion section interprets the model's structure, reflects on its implications, and evaluates its limitations and potential extensions in terms of future research.

5.1. Interpretation of the Model

When it comes to the dimensions highlighted in the ESAIMM, many non-industry specific dimensions appear such as with data, strategy & leadership as well as human & organizational capability. This is because while the energy utilities industry does have an array of unique problems, there simultaneously exists much in common with other industries. The foundations for AI can therefore be extrapolated to be universal across industries. Data related issues specifically appeared as a key challenge in energy utilities, as is consistent with the literature both within the focus sector as well as universal to most other industries (IEA, 2025). Data readiness, siloed data, and the interoperability of data between IT/OT systems exist as particularly poignant for energy utilities organizations. This is likely due to the fact that while the energy utilities industry is known for producing vast amounts of data through IoT and sensor integration in operational systems, there are often issues with utilising said data due to low quality, incompleteness or the overall fragmented organizational data. Given the aging and legacy infrastructure of the industry, issues with IT/OT convergence are another common obstacle particularly for industry specific use-cases. These areas of concern are reflected through the data foundations and technology & infrastructure of the ESAIMM, with primary points of emphasis in maturity relating to IT/OT convergence, data governance, real-time analytics, and data interoperability.

Conversely, internal capability dimensions exhibit compared to the technical and alignment dimensions far lower sector specificity. However, far from indicating lesser significance, this stems from their alignment with ubiquitous organizational challenges prevalent across industries. People can therefore be considered a core pillar for successful adoption and utilization, as is encompassed in most AIMMs. This dimension is especially foundational in regard to talent, training, and change management. Each of which are fundamental and therefore are displayed alongside the technological dimensions as a core dimension of AI maturity.

The alignment dimensions, similarly, to its technological counterpart, possess a combination of universal and industry specific dimensions and subsequent indicators. A particular area of importance being that of the risk management and ethics dimension, due to the criticality of energy utilities and compliance with regulations such as the AIA. Furthermore, with the key role that energy players have in enabling decarbonization and adapting to the increasing complexity they face with DERs, modular networks, cybersecurity risks, this dimension accounts for the key external challenges and opportunities energy organizations face. A challenging future where collaboration and partnerships will be necessary for trust, innovation and competitiveness. These dimensions consequently best reflect the long-term facets for competitive and long-term success for organizations within the industry.

A recurring theme across the ESAIMM indicators is the emphasis on continuous monitoring and refinement, high-ROI and scalable initiatives, and strategic adaptability to change within energy organizations. This constitutes the essential foundation for energy utilities navigating their current era of profound transformation. Organizations should therefore cultivate cross-functional ecosystems, forging alliances with regulators, innovators, start-ups and data-sharing consortia to harness collective intelligence for grid resilience and decarbonization.

5.2. Contribution & Limitations

The ESAIMM developed addresses the gap in the existing literature by providing an AIMM specifically tailored to EU energy utilities. Unlike prior frameworks that target narrow domains, such as RAI or technical integration, the ESAIMM provides a holistic perspective integrating the sector's unique challenges, including regulatory flux (e.g., AI Act and GDPR)

and OT/IT convergence. The artifact developed provides therefore a systematic tool for energy stakeholders to assess and develop AI capability.

However, there are certain limitations which must be acknowledged in terms of the robustness and completeness of the artifact presented. As previously stated, the AIMM created acts as a preliminary model, since the dimensions and indicators were derived mainly from existing literature and refined through limited qualitative analysis, the artifact constitutes a preliminary AI maturity assessment model rather than a fully validated instrument.

Furthermore, since the scope of the study is focused on the EU-context, findings may not be directly transferrable to other regions or contexts. Moreover, given the evolving and partly ambiguous nature of EU regulation, as well as the deliberate delimitation of the regulatory frameworks considered in model development (the AI Act and GDPR), the model does not claim to provide comprehensive regulatory certification.

Future research should pursue rigorous empirical validation of the model through the active involvement of diverse stakeholders across the energy utilities industry. Furthermore, extending the model into a practical benchmarking tool would enhance its applicability by enabling stakeholders to assess AI maturity within their specific contexts.

6. Conclusion

This study set out to develop and evaluate a maturity model for AI governance and diffusion in the energy sector, with the aim of explaining how organizations can manage complexity, risk, and value when integrating AI across an organizations operations and business units. The core dimensions of AI maturity through literature synthesis and thematic analysis were found to be Workflows & Impact Assessment, Organizational & Human Capability, Strategy & Leadership, Risk Management & Ethics, External Stakeholders, Data Foundations, and Technology & Infrastructure. These dimensions were further categorized into the three areas of Internal Capabilities, Alignment Dimensions, and Technical Capabilities, where internal and technical capabilities were found to foundational to successful AI diffusion. For energy organizations, the model provides a diagnostic tool to assess current AI maturity, identify priority gaps, and design targeted roadmaps for governance, data infrastructure, and autonomous operations. Moreover, by linking AI maturity to collaborative partnerships, sustainability, cybersecurity, and RAI, the model also supports the broader energy transition, helping regulators and utilities to balance innovation with risk and societal expectations. However, the generalizability of the model is constrained by the limited sample and qualitative nature of the current version of the artifact. Future research should therefore validate the model with a varied and significant number of energy stakeholders, link and test against performance metrics, and test its applicability across different organizational contexts.

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Appendix 1. Synthesis of AI Maturity Model Dimensions

Authors	Number of Dimensions	Source	Purpose/Scope	Form	Dimensions
Akbarighatar et al., 2023	2, 16 sub-dimensions	Journal Article	Responsible AI	Text	Two Main Categories: Foundational (Data Quality, Data Availablility, Financial Capability, Organizational Strategic Planning, Innovation Management, Change Management, Human Resource Management, Interdepartmental Coordination, Performance Of Ai Systems) And Responsible Ai Capabilities (Security, Continuous Impact Analysis, Employee Ethical Awareness, Privacy, Fairness Evaluations, Transperancy Of AI Models, Accountability
Armutat et al., 2025	3, 18 sub-dimensions	Journal Article	GenAI corporate competency	Table	Digital/Technological, Social, and Cognitive Competency
Behnaz, 2026	7	Industry	GenAI	Model	Strategy, Technology, Governance, People, Customer, Financial & Legal, Supply Chain

Bloedorn et al., 2023	6, 20 sub-dimensions	Industry	General	Model	Ethical, Equitable, and Responsible Use, Strategy and Resources, Organization, Technology, Enablers, Data Performance and Application
Butler et al., 2023	6	Journal Article	General	Table	Business, Data. Technology, Organisation, AI Knowledge and Skills, Ethics and Risks
Colangelo et al., 2022	5, 18 sub-dimensions	Journal Article	Production Planning and Control (PPC)	Model	(General) Strategy and Vision, Investment Readiness, Use Cases, (Data)Data Quality, Data Demand Transparency, Historical Data, PPC Data, Cross-divisional Data, (PPC) PPC Understanding, (Technology) Machine Integration, PPC Systems, AI Technology, Enterprise Data Management Systems, Automation of Data Acquisition, (Organisation) Process Structure, Expert Knowledge of AI, Readiness for Change
Di Chiacchio et al., 2026	3	Journal Article	Trustworthy AI in Energy Sector	Table, Model	Alignment with SDG7 and Responsible AI Governance,

					Developing Trustworthy and Accountable Narratives, Establishing Stakeholder Trust and Organisational Legitimacy
Eliseo et al., 2025	9	Journal Article	Industry 4.0	Table, Questionnaire, radar chart	Strategy and Organization, Processes, Customers, Technology, Data (Monitoring and Control), People (Workforce), Products and Service, Manufacturing and Operations, Operational technology
Fornasiero et al., 2025	5	Journal Article	Big data in process industry	Table, Model, Questionnaire	Strategy, People, Decisions, Data, and Analytics
Gartner	7	Industry	General	Text	Strategy, Product/Use Case Portfolio, Data Sources, Engineering, AI Governance, Operating Models, Culture and Skills
Hansen et al., 2024	3	Journal Article	Diffusion of AI	Text	Technological Dimension, Organizational Dimension, External Dimension
Heger et al., 2025	3, 24 sub-dimensions	Journal Article	Responsible AI	Table	Organizational Foundations, Team Approach, and RAI Practices
IBM, 2023	8	Industry whitepaper	Energy sector	Model	Strategy and leadership, organization and culture, technology, sustainability, grid operations, work and

					asset management, customer experience, and market innovation
Krijger et al., 2023	6	Journal Article (opinion paper)	Organizational AI ethics	Model	Awareness and Culture, Policy, Governance, Communication & Training, Development processes and Tooling
Luget et al., 2025	4	Industry	Responsible AI	Model	Strategy, Risk Management, Data And Technology, Operating Model, Talent And Change Management
McCormack and Bendechache, 2026	7	Journal Article	Trustworthy AI	Table, Questionnaire	Human Agency, Technical Robustness, Privacy, Transparency, Fairness, Societal Well-Being, And Accountabiliy
Muñoz-Ordóñez et al., 2025	3	Journal Article	Explainability maturity	Table	Technical Foundations, Structured Design, and Human-Centered Explainability
Sadiq et al., 2021	7	Journal Article	SLR of AIMMs	Text	Data, Analytics, Technology and Tools, Intelligent Automation, Governance, People, and Organization
Sonntag et al., 2024	5	Journal Article	Manufacturing	Table	Culture & Competencies, Strategy, Data, Organization & Processes, Technology
Winby and Xu, 2026	4	Journal Article	Human-centered AI	Table, Model	Governance, Stakeholder

					Engagement, Training and Education, Impact Assessment
Wynter, 2025	7	Journal Article	Strategic AI	Model, Radar chart	Strategic AI Alignment, Executive Leadership and Strategic Competence, Governance, Ethics and Responsible AI, Organizational Design and Operating Model Adaptation, Culture, Mindset and Change Readiness, AI Value Realization and Strategic Impact, AI Roadmap Execution and Strategic Planning Capability

Appendix 2. Thematic Interview Questions

Data, information management, and technical infrastructure/Data, tiedonhallinta ja tekninen infrastruktuuri

- What are the key data foundations and technical infrastructures that lay the foundation for successful AI deployment? /Mitkä ovat keskeiset dataperusteet ja tekniset infrastruktuurit, jotka muodostavat pohjan onnistuneelle AI:n käyttöönotolle?

Culture, internal capability, and accountability/Organisaatiokulttuuri, osaaminen ja vastuut

- What do you believe are the critical facets of human capital and internal processes that are a part of AI deployment/Mitkä ovat mielestäsi ne keskeiset työvoiman ja sisäisten prosessien osa-alueet, jotka ovat osa tekoälyn käyttöönottoa?

Risk management and AI Act alignment/Riskienhallinta ja AI Act -vaatimukset

- How would you evaluate their significance, especially their weight compared to other dimensions/Miten arviosit niiden merkityksen, erityisesti niiden painoarvon verrattuna muihin ulottuvuuksiin?
- How are these currently considered and taken into account with AI diffusion in the energy sector?/ Kuinka näitä huomioidaan tällä hetkellä AI:n integroinnissa energia-alalla?

Areas for improvements and wishes for the model/Tulevaisuuden kehitystarpeet ja toiveet mallille

- What do you consider as especially imperative for future development and successful AI deployment within the energy industry/ Mitä pidät erityisen välttämättömänä tulevaisuuden kehityksen ja tekoälyn onnistuneen käyttöönoton kannalta energia-alalla

Feedback on the maturity model/Palaute maturiteettimallista

- What dimensions of the maturity model feel fitting, are missing or feel unclear?/Mitkä prosessialueet tuntuvat osuvilta, mitkä puuttuvat, mitkä ovat epäselviä?