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Citation for the original published paper (version of record):
Persson Schön, P., Bergsjö, D. (2025). Leveraging AI to Enhance Systems Engineering Practices in Large-Scale Infrastructure Projects. IEEE International Symposium on Systems Engineering (ISSE).
http://dx.doi.org/10.1109/ISSE65546.2025.11370113

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Leveraging AI to Enhance Systems Engineering Practices in Large-Scale Infrastructure Projects

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2025 IEEE International Symposium on Systems Engineering (ISSE) | 979-8-3315-7550-2/25/$31.00 ©2025 IEEE | DOI: 10.1109/ISSE65546.2025.11370113

Abstract*— *The increasing complexity of large-scale infrastructure projects presents significant challenges and specifically challenges in Systems Engineering (SE) activities, particularly in managing vast volumes of data, evolving stakeholder requirements, and maintaining traceability across long project lifecycles. This study explores the potential of Artificial Intelligence (AI), particularly tools based on Natural Language Processing, to support SE practices in infrastructure contexts. Through a combination of survey data, two pilot studies, and five semi-structured interviews conducted within the Swedish national transport administration, the research investigates how AI can improve system information management, assist with Systems Engineering tasks, and what practical barriers limit broader adoption. Findings indicate that AI tools show promise in supporting text-heavy SE tasks such as document summarization, requirement tracking, and assumption analysis. However, low organizational awareness, trust concerns, lack of integration into workflows, and restricted access to internal data due to security concerns significantly limit their current impact. The study concludes by recommending targeted organizational strategies, operational support roles, and structured experimentation to unlock the full potential of AI in supporting SE in large-scale infrastructure projects.

***Keywords*—** *Artificial Intelligence (AI), Systems Engineering, Infrastructure Projects, Natural Language Processing (NLP), Requirement Management, Sociotechnical Systems*

I. Introduction

Mega projects take up an increasing part of the total global GDP [1]. Mega infrastructure projects are increasingly complex due to an increasing number of parameters, such as involved stakeholders, more regulations, larger organizations, and technical development, explained by Cantarelli et al. [2] as technical, economic, psychological, and political aspects. With an increasing number of parameters, components and interfaces, the structural complexity of the system increases superlinearly [3], Figure 1. The architecture of the system goes towards a distributed architecture rather than a centralized meaning that the dependencies of the parameters in the system are dependent on each other in a complex or "messy" way rather than a linear or hierarchical way. This complexity also increases and correlates with the cost of the system or project [3].

These infrastructure projects also produce an increasing amount of data, which is a symptom of the complexity but further drives it. The amount of data in the projects has increased both over time and with the size of the project. According to Boamah, et al. [4] 95% of the project data cannot be handled with standard knowledge retrieval methods.

Especially security-classified projects, which have had a rapid rise in engineering projects [5], must manage the data carefully. Often, parts of a megaproject are security critical and therefore, parts of the data must be managed as such, which also adds to the complexity of managing the project.

Infrastructure projects are characterized by a growing number of parameters, increasing system complexity, and vast volumes of data that must be effectively managed by organizations. In a study seeking the design-construction integration problems in large infrastructure projects Sha'ar, et al. [6] found *Unstable client requirements* and *Lack of proper coordination between various disciplines of design team* as the top two problems. Systems Engineering (SE) provides a structured methodology to address such challenges, emphasizing requirements management, stakeholder engagement, and system integration. While some SE practices are applied within Swedish construction projects, there is currently no overarching SE strategy or designated responsibility for its implementation. For complex rail projects, which take up a significant part of infrastructure mega projects, Persson, et al. [7] shows that there is a lack of consensus on SE practices and terminology, and therefore a need for standardized approaches.

Historically, the design leader, who is responsible for most of the systems engineer activities, might have been able to manage system-level coordination independently. However, the scope and complexity of today's projects have made this increasingly unfeasible. As one actor in the civil engineering

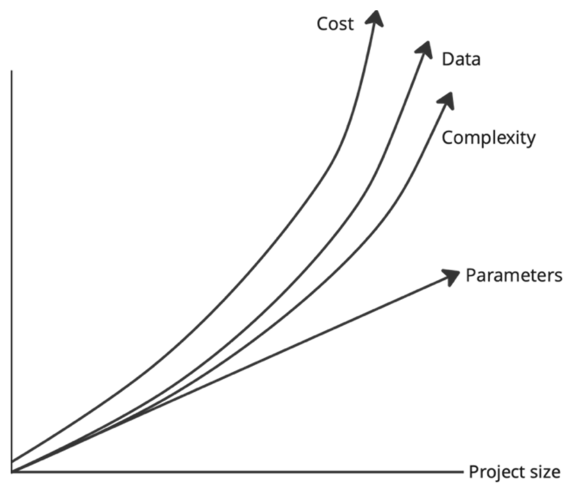

Figure 1. Schematic illustration showing how a growing number of parameters drives project size, which in turn leads to accelerating increases in complexity, data volume, and cost.

sector expressed in an interview from an unpublished study: "*Twenty years ago, the design leader could have some control over the system, the requirements, and the decisions being made. Today, the design leader is more of an advanced administrator who does not, and perhaps cannot, maintain control over the system's design. There is simply too much happening at the same time.*" Robinson [8] demonstrates that design engineers spend 20 % of their time *understanding information* and 18 % of their time on *problem-solving*.

In other words, the exponential growth in data, the continual evolution of standards, and the increasing diversity of stakeholder requirements often exceed the capacity of traditional SE approaches to cope effectively. Without suitable tools and support systems, systems engineers are exposed to greater risks, including scope creep, late-stage design changes, and cost and schedule overruns.

A. Artificial Intelligence

Artificial Intelligence (AI), and in particular Natural Language Processing (NLP), Machine Learning (ML), and Large Language Models (LLMs), present promising tools that support SE practices. NLP refers to computational techniques for understanding and generating human language, enabling the automated processing of unstructured text data [9], while ML encompasses algorithms that learn patterns from data to make predictions or classifications without being explicitly programmed[10]. LLMs are large-scale neural network models trained on extensive text corpora to generate coherent and contextually relevant language, which can be used for tasks such as summarization, question answering, and drafting documentation [11]. A related approach, Retrieval-Augmented Generation (RAG), combines an LLM with a retrieval mechanism that first searches relevant documents before generating a response, improving factual accuracy and transparency.

AI can assist in automating the analysis of extensive documentation, identifying inconsistencies, and facilitating decision-making processes [12]. AI's potential in optimizing design processes, managing construction workflows, and supporting requirements engineering could play a significant role in the future of SE in infrastructure contexts. There is a pressing need to explore how AI can be effectively harnessed to support systems engineers in managing the increasing complexity and information overload inherent in contemporary infrastructure development.

B. Systems Engineering in infrastructure projects

Infrastructure projects are not static endeavors, they evolve over time, moving from contract formulation and early design phases to detailed concept development and legal documentation. A large number of individuals are involved throughout the project lifecycle. As the project advances, the number of active actors increases significantly, particularly during the design phase when the integration of contractual requirements, technical standards, and evolving project constraints must be managed simultaneously. This multi-layered, multi-actor landscape leads to information fragmentation, coordination challenges, and increased risk of miscommunication.

The number of actors, combined with the growing complexity of regulatory and technical environments, creates an urgent need for tools that can assist in structuring, retrieving, and synthesizing information. While AI has been increasingly applied in construction design for safety monitoring, process management, cost estimation, and quality assessment [13], its potential to support daily Systems Engineering activities in infrastructure projects remains underexplored. Previous reviews primarily focus on technical optimization and automation within discrete tasks, but do not sufficiently address how AI could assist design leads and systems engineers in interpreting requirements, cross-validating expert inputs, or managing large volumes of technical documentation. AI, particularly tools powered by NLP, offers an opportunity to support systems engineers by systematically navigating contractual documents, technical standards, and design outputs. AI tools can thus serve as a digital assistant, improving information management across diverse teams and supporting more consistent decision-making in large-scale infrastructure projects.

C. AI as support for organizations and Systems Engineering practices

AI and ML into systems engineering practices is not seen as an enhancement of existing capabilities but rather a paradigm shift in the approach of designing, managing, and optimizing complex systems and project management [14] [15]. AI can enhance the full lifecycle management of a system, from the design to the finalized system. Mueller and and Chiou [16] suggest that AI should not be seen as a tool but rather as an integrated teammate. AI can enhance the accuracy of forecasting, improve stakeholder collaboration, and risk mitigation [15]. Boamah, et al. [4] states that AI should not be designed to replace current knowledge systems, as, especially in infrastructure projects, there is a lot of industry-specific insight built into the knowledge system.

There are some ethical and societal issues, for example biases in decision making, and impact on employment [14]. Other barriers are high cost, resistance to change, and legacy system integration [15]. These barriers, together with the rapid development of AI demand an evolution in the education and training of systems engineers, and ethical frameworks need to be developed and tailored to interpretability solutions [4]. Salimimoghadam, et al. [15] encourages small-scale pilots to build confidence for the practitioners with established feedback loops on the performance of the tools. The users understanding for the tool and the interpretability of AI systems is a top priority to ensure that the user trusts the solutions [4].

Given this context, we conducted a focused study within one organization, the Swedish Transport Administration, which is responsible for the full lifecycle management of railway and national roads in Sweden. This study complements earlier work by examining how AI tools could be used not only for automation but also for cognitive support, traceability, and informed decision-making throughout the design process, activities that are central to successful Systems Engineering in large-scale infrastructure projects. This paper aims to explore and evaluate the use of AI tools to support Systems Engineering activities in infrastructure projects.

D. Research Questions

- RQ1: How can AI-based tools improve the management of system information in infrastructure projects?
- RQ2: In what ways can AI assist in core Systems Engineering tasks (such as handling requirements, standards, and project documentation)?
- RQ3: What are the limitations and practical challenges of applying AI in real project settings?

Table 1. Overview of interview participants, their roles, and the AI tools they tested during or before the study.

Interviewee	Role	Tool
A	Project engineer	NotebookLM
B	Design leader	NotebookLM
C	Design leader	ChatGPT
D	Design coordinator	NotebookLM and ChatGPT
E	Design coordinator	NotebookLM

II. METHODOLOGY

To answer the research questions, this study involves mainly three main activities: a survey, interviews, and two pilots that were all conducted at the Swedish Transport Administration. An additional interview with an external security expert at a construction company was also conducted.

A. Surveys

A survey was conducted in two master's theses in the spring of 2025, and the relevant data are presented in this article. In total, 61 people working with large infrastructure projects in Sweden answered questions with the aim of exploring challenges and possibilities of implementing AI practices in large infrastructure projects.

B. Interviews

Five interviews were conducted with people within the organization who had tried different AI tools, *Table 1*. These interviews aimed to explore challenges and possibilities based on real-life experience. The questions in the interviews were designed based Technology Acceptence Model (TAM) and Sociotechnincal Systems Theory (STS). TAM was introduced by Davis [17], which describes its two key elements: Perceived Usefulness, the degree to which a person believes that using a particular system would enhance their job performance, and Perceived Ease of Use, the degree to which using a particular system would be free from effort. STS was applied with the aim of understanding how AI tools correlate with organizational and social factors, including culture, competence, and technical [18]. The interviews were semi-structured, and the interviewees had a role similar to a Systems Engineering role, as System Engineer is not a defined role in the organization.

One interview, interviewee F, was conducted with a security expert at a construction company. This interview aimed to get insights into the security aspects of AI. The result from this interview is presented separately from the other.

C. Pilots

Two pilots were conducted. The first pilot explored if and how reports and descriptions from earlier projects could be utilized in new projects. In this case, seven "Environmental Impact Assessment" (EIA), was utilized as a support in the development of the EIA´s for ongoing projects. EIA´s are reports regarding the environmental impact of an infrastructure project. In large projects, they are almost always mandatory and takes up a large part of the resources and time of the concept phase in the project.

The second case aimed to support the control of a contract, a "contract chatbot". Parts of the project management team for the client was given a "chatbot" for their contract. The documents that are in the contract were utilized for the project management team to ask questions to support their everyday activities. The contract is the fundamental part of a project when a client utilizes an actor to carry through the project. In large infrastructure projects, there are often lots of contracts for different actors in different phases. Each contract could refer to 300-500 other documents, which are therefore included in the contract. In each contract, there are ongoing changes to the contract, both formal, when time, cost, and content are changed, and informal, when the organizations interprets the contract and sometimes takes shortcuts in the project.

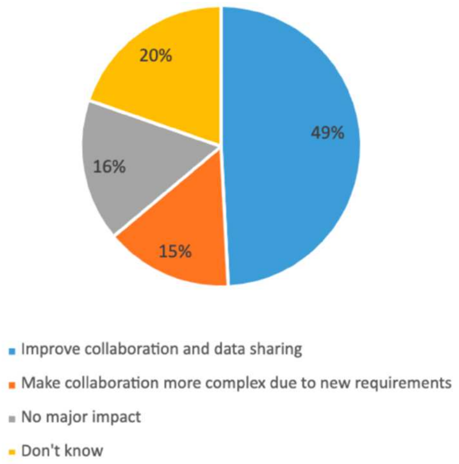

Figure 2. Survey responses on how AI tools are expected to impact collaboration with external stakeholders.

In both pilots, Google's NotebookLM was utilized. NotebookLM is an experimental AI-powered notebook developed by Google. It leverages LLMs in combination with RAG techniques to assist users in synthesizing information from their own documents, effectively acting as a personalized research assistant. In this study, NotebookLM was employed to process and analyze various project documents, including contracts, environmental reports, and regulatory standards. The tool's combined capabilities in natural language processing, information retrieval, and grounded text generation were assessed to determine its effectiveness in supporting SE tasks such as requirement analysis, compliance checking, and decision-making.

III. RESULTS

A. Survey

Respondents were also asked how they believe AI could impact collaboration with external stakeholders, Figure 2. Almost half, 49%, indicated that AI could enhance collaboration and data sharing, while 15% believed it might increase complexity in external interactions.

When asked about their familiarity with the organization's work on AI, 56% of respondents stated that they were not familiar at all, Figure 3. Regarding factors contributing to resistance toward AI within the organization, the most frequently mentioned were a lack of knowledge and low trust in AI-generated decisions, Figure 4.

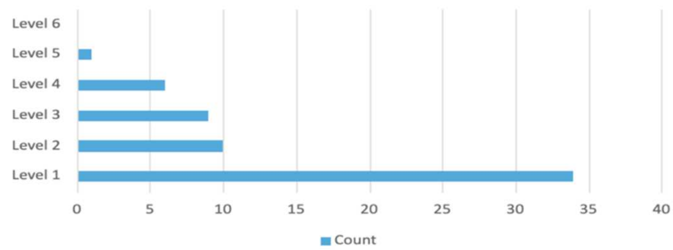

Figure 3. Respondents' awareness of their organization's work with AI.

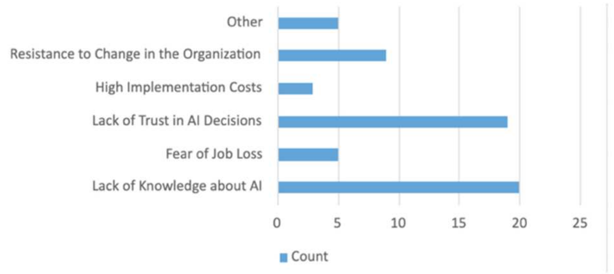

Figure 4. Barriers to AI adoption in the organization, including lack of knowledge, trust issues, and perceived risks.

When asked how AI should be implemented within the organization, Table 2, the most supported suggestion was that management should provide clear communication about AI's role and purpose. This was followed by the need for training and skills development, clear guidelines, and support from AI experts.

Table 2. Ranked suggestions from survey respondents on how their organization can support the adoption of AI tools

Rank	Suggestion
1	Clear communication and support from management regarding the role and purpose of AI
2	Training and skills development for employees
3	Clear guidelines and strategies for AI usage
4	Support from AI experts
5	Security and privacy (I want to know that AI cannot be abused or manipulated)
6	An AI that is transparent about how it makes decisions
7	I want AI to always be monitored by a human
8	Opportunities for employees to influence and be involved in the implementation of AI processes
9	Nothing in particular, I already feel confident

B. *Interviews*

Three of the interviewees had tried different AI tools for professional use, mainly ChatGPT and NotebookLM had given the best experience. Other tools, such as Microsoft Copilot had briefly been tried. Three of the interviewees had been given the task to test the pilot where NotebookLM was utilized as a contract chatbot. Their overall result from the interviews is presented in this section, and some specific results regarding the pilot contract chatbot are presented in section *C. Pilots*. The result from an interview with a security expert at Construction Company is presented separately from the other interviews.

1) Usefulness and Usability of AI Tools

All interviewees described some level of uncertainty regarding the accuracy of AI-generated answers. They stated that they could not fully rely on the tools to produce correct results. Despite this, all interviewees described the tools, such as ChatGPT and NotebookLM, as relatively easy to use. Some functions, especially in NotebookLM, were described as unclear, but at the same time, NotebookLM's presentation of source material contributed positively to the understanding of where information came from.

Interviewee A said that the contract chatbot that utilized NotebookLM was slow and that it was faster to retrieve the information manually. However, interviewee B noted that the tool supported information retrieval when the same topic was described in multiple documents, faster and more accurately than he himself could retrieve the information.

All the interviewees stated that the AI tools have only been used for basic tasks, including summarizing contract content, comparing versions of documents, drafting short texts, and retrieving information about specific topics. Interviewees D and E had used AI to examine differences between versions of a technical standard, explore alternative formulations of contract clauses, and draft a role description. Interviewee E has used NotebookLM to analyze documents with a lot of information, getting summaries and insights to develop the ways of working in ongoing projects. She estimates that AI could be used in 20% of everyday work.

Several interviewees noted that concerns related to trust in the answers, data security, hallucination, and uncertainty around prompt formulation had influenced how useful they considered the tools to be. All the interviewees stated that they have a general skepticism about the answers from the AI tool and that they does not trust the tool to provide the right answer. Again, the fact that NotebookLM shows the source for the answers in detail was expressed by all the interviewees who had tried NotebookLM as a key feature to increase the trustworthiness and use of the answers. For example, Interviewee B, who used NotebookLM in the contract chatbot pilot to understand information stated in several sources, stated that he could get a quick overview of a topic and then go into detail in the specific sources.

2) Individual and organizational preconditions for the use of AI tools

All interviewees expressed a need for support regarding how the tools could be applied in their day-to-day tasks. They specifically mentioned a lack of knowledge around how to formulate prompts. Interviewee D stated that the range of possible applications was perceived as so broad that it became difficult to know where to begin. This interviewee expressed a wish for more concrete examples and suggestions for how to approach the tools in practice. Other interviewees expressed similar needs.

Interviewee D described a preference for having a "superuser", a dedicated person within the department who could provide support locally, rather than attending general presentations that were not perceived as adapted to their professional context. The same interviewee also mentioned a need for financial resources to obtain access to the tools.

Interviewee A emphasized that it would be helpful to start by identifying time-consuming activities in everyday work and explore those areas first, before introducing AI tools.

3) Sociotechnical Integration and reflection of change

All interviewees described AI as something that could be used in new ways of working. At the same time, they described a lack of clear strategies or designated responsibilities for how AI should be used in the organization. Interviewee E sees herself as an ambassador to promote the use of AI tools.

Interviewee C referred to the introduction of the internet as a comparable situation, stating that AI is sometimes seen as a solution to many problems, but that it is often unclear how it is meant to be used, by whom, or for what purposes. The same questions as when the internet was widely introduced.

Some interviewees described that AI use remains isolated and informal, and expressed a view that broader use may require integration into workflows and organizational practices. Others stated that questions remain about how such integration should be carried out and who should be responsible for it.

Most of the interviewees would like to see a tool that is specifically developed for the organization. Interviewee C stresses that an internal solution that could be used for all the internal material would give possibilities that an external tool could never give, as the context is so specific for the organization. Interviewee B states that if it were possible to use an AI that could use all the internal documentation in the project as a source, the benefits would be huge.

4) Security aspects

Security-classified projects require careful management of protected information such as sensitive data, technical documentation, and personal records. This information must be handled using approved IT systems with strict control over server locations, user access, and physical storage, often within dedicated secure environments. Personnel involved typically undergo extensive security screening, which can increase both project costs and lead times.

A persistent challenge lies in the lack of universally defined criteria for what qualifies as protected information. As a result, individual projects must interpret and implement security requirements independently, which often leads to inefficiencies and delays. Interviewee F revealed that this lack of clarity around a project's security level is frequently a limiting factor in project execution. In contrast, projects that do contain clearly defined restricted or classified elements tend to encounter fewer issues, as the separation between protected and non-protected parts is well understood and managed through dedicated systems.

Although many projects are not formally classified, there is an increasing trend toward applying baseline security practices more broadly, driven by rising concerns over information vulnerability. While digital tools and AI are being considered for improving security processes, their use in sensitive projects remains limited due to regulatory constraints. Cloud-based solutions, for example, are frequently restricted unless they conform to national security guidelines. These conditions point to the need for clearer regulations, shared definitions, and standardized procedures that can support both compliance and technological innovation in secure project environment.

C. Pilots

1) Using AI for Document Analysis and Decision Support

A pilot was conducted to evaluate how an AI-based system could support decision-making by analyzing Environmental Impact Assessment (EIA) documents. The AI tool, utilizing NotebookLM, was used to answer a scenario-based question about noise mitigation in densely populated areas. The system extracted structured answers from uploaded documents, presenting categorized information with source references and highlighted text segments.

The AI responses listed common noise measures used in previous railway projects, including trackside barriers, property-near solutions, and restrictions during construction. The tool referenced real projects and organized the output by phase (e.g., operational vs. construction), showing how certain measures were applied depending on project characteristics.

A validation process showed that the AI tool only used uploaded documents and consistently linked statements to verifiable sources. However, repeated content and generalizations were observed, especially when questions sought recommendations. A comparison with a real EIA from a mega project showed that while the AI captured standard practices, it missed some project-specific considerations.

An expert assessment confirmed the usefulness of the tool for background work and general references, especially in early project phases. However, project-specific investigations are still required for detailed analysis and decision-making. The expert highlighted the tool's potential for enhancing experience feedback and streamlining early-phase planning work.

2) Using AI as a Contract chatbot

This pilot study explored how an AI-based chatbot could support work with contract documents in infrastructure projects. This pilot also utilized NotebookLM. The tool was trained on a set of documents for a project contract and allowed users to ask natural-language questions to retrieve or clarify contract content. Three of the interviewees, A, B, and D, tried the contract chatbot.

The chatbot was described as intuitive and easy to interact with. However, users expressed general uncertainty about the accuracy and reliability of the answers. While the interface was clear, several responses were perceived as either repetitive or insufficiently specific, especially when questions were nuanced.

Interviewee B described the chatbot as helpful for comparing different versions of contract clauses and for identifying specific terms across documents. The tool was used to draft explanatory text and to explore how certain requirements were expressed in different contexts. Interviewee A noted that for simpler tasks, it was sometimes faster to search manually than to rely on the chatbot’s output. Despite this, the tool was seen as more valuable for tasks involving larger volumes of text or when familiarity with the documents was low.

All three participants emphasized that the tool was most useful for retrieving information and preparing summaries, but not for drawing conclusions or making decisions based on the content. It was noted that effectiveness could improve with clearer prompt strategies and concrete examples of use. The pilot indicates that AI-supported chatbots have potential as a support tool for navigating complex and voluminous contract documents. However, issues related to trust, response accuracy, and integration into daily work need to be addressed for broader organizational use.

IV. Disscussion

AI as a support for Systems Engineering activities shows significant potential in construction projects. However, the paradigm shift expressed by Adeyeye and Akanbi [14] and Salimimoghadam, et al. [15] does not happen by itself. It must be encouraged and facilitated by the organization. This study has identified some challenges but also presents some guidance on what could be done.

A. Challenges for the organization regarding AI tools that could support SE practices

Large infrastructure projects are characterized by long lifecycles, extensive documentation, and numerous actors.

Systems Engineering (SE) offers a structured approach for managing such complexity across the system's life cycle, but these conditions create significant challenges for information and knowledge management. As projects progress, information increases both in volume and in interconnections. The resulting information management, combined with long project durations, poses a challenge to traceability, consistency, and hence the ability to perform informed decision-making.

AI-based tools present a promising complement to SE practices by facilitating tasks such as document analysis, consistency checks, and synthesis of stakeholder requirements. Nevertheless, findings from both the survey and the interviews suggest that trust in AI tools remains limited. This distrust comes from a lack of transparency in how the tools work (the "black box" problem) as well as limited user familiarity and knowledge about appropriate use cases. Several interviewees explicitly stated that they cannot rely on the tools to produce correct answers without verification, and survey respondents indicated that low trust and insufficient knowledge are primary barriers to adoption. This skepticism and the expressed need for training align with the Technology Acceptance Model (TAM), where perceived usefulness and trust are key determinants influencing users' intention to adopt new technologies. These challenges are especially hard to manage for security-classified projects or data.

NotebookLM is experienced as more trustworthy than other alternatives. The answers from ChatGPT are sometimes seen as wrong, hallucinations, or not relevant by the user, are harder to verify, and therefore not as useful as NotebookLM. Part of this higher trust can be attributed to the RAG architecture by NotebookLM. By combining the retrieval of relevant text passages from uploaded documents with generative outputs, RAG makes it possible for users to trace the origin of information, which directly addresses the transparency gap often cited as a barrier to AI adoption. Several interviewees highlighted this feature as critical for validating content and improving confidence in AI-assisted tasks.

Further, the organization lacks internal structures to support effective AI use. This is a classic socio-technical misalignment as the technology advances, but the organization and it structures lags behind. More than half of the survey participants reported being unaware of the organization's AI-related initiatives. Interviewees raised questions regarding what they are permitted to do with AI tools, particularly when handling internal or sensitive documents. Across the interviews, a recurring theme was the lack of support for how to use the tools effectively, particularly in terms of prompting techniques, understanding tool limitations, and identifying suitable use cases.

The organization appears to be disconnected between individual experimentation and formal strategy. AI use is currently emerging from unstructured bottom-up initiatives as individuals test tools independently without shared learning or coordination. At the same time, there are signs of a top-down strategic interest in AI, but this has not yet translated into actionable guidance or operational support for those working in projects. This results in a gap between intention and implementation, where organizational ambitions for AI remain unconnected from real project needs and practices. In this state, AI cannot yet fulfill its potential to support SE activities such as requirements tracing, document versioning, and knowledge synthesis.

B. *What could be done in the future?*

To close the gap between AI potential and current use, the organization needs to have both a strategic ambition and operational experimentation. Although the pilots in this study were limited in scope, they provided valuable insight to the individuals involved. These cases illustrate that even small-scale pilots can generate learning, interest, and practical understanding, especially when directly embedded in real project tasks. However, in the absence of formal processes to capture and disseminate insights, the practical value of such pilots remains largely anecdotal and difficult to translate into organizational improvement. Without attention and reflection, the knowledge generated remains isolated and cannot contribute to organizational learning.

Rather than solely pursuing broad top-down strategies, the organization could benefit from supporting local experimentation through structured bottom-up initiatives. Mueller and and Chiou [16] came to the same conclusion researching the use of AI in higher education, that *"Embrace a blended approach of bottom-up experimentation and top-down strategic planning in AI implementation, fostering innovation while ensuring cohesive institutional strategies and principled innovation"*. Such an approach requires clear guidance, including what kinds of tasks AI tools can support, how users should evaluate outputs, and what internal policies govern tool usage, especially when internal data is involved. This guidance should be accompanied by practical training and example libraries, addressing the knowledge gaps related to prompt formulation and appropriate applications.

In parallel, creating support structures, such as assigning superusers or a AI-competent points of contact within departments, could help bridge the knowledge and confidence gaps that were frequently cited in the interviews. This further confirms Mueller and and Chiou [16] recommendation of dedicated support staff and feedback mechanisms within the organization. Furthermore, internal discussions around ethical, legal, and procedural questions must be initiated, particularly as AI tools begin to interact with sensitive documents and decision-making processes.

For AI to become a useful part of SE practices, it must be integrated into workflows and not seen as an external or experimental activity. Several interviewees noted that while AI tools might save time or enhance understanding, they were unsure how to embed them into their professional routines. Addressing this uncertainty requires leadership to prioritize integration, not just access to tools. By doing so, AI could move from being something unknown and frightening to becoming an integrated teammate and a core enabler of improved systems thinking and information management in infrastructure projects.

C. *Limitations and reflections about the research*

This exploratory study aimed to provide an initial understanding of how AI may influence work practices in infrastructure projects. However, the empirical foundation is limited as only five interviews were conducted, the survey received 61 responses, and the two pilot studies were small in scope. In addition, all data were collected within a single organization, which limits the generalizability of the findings and introduces a risk of organizational bias. This study may not represent the entire global infrastructure sector. However, since AI is developing quickly and likely marks a major paradigm shift [14] [15], research needs to be done, published, and findings need to be shared step by step.

The organization under study is in an early phase of AI adoption, with no established SE framework, which further constrains the interpretive validity of the results. Despite these limitations, the study has generated practical insights that are currently being used to inform internal organizational efforts. This creates an opportunity for future follow-up research that can build on a broader empirical base, include additional actors, and apply more rigorous evaluation methods. Given that the organization plays a central role in Sweden's infrastructure sector, managing projects amounting to approximately one percent of the national GDP [19], continued research in this context could have significant implications. However, such impact must be grounded in methodologically robust studies across multiple contexts.

Security concerns related to AI use in infrastructure projects have been acknowledged and briefly addressed in this study. While data protection and system integrity are undeniably important, the researcher's experience suggests that such issues often dominate top-down initiatives within large organizations. In contrast, bottom-up experimentation, driven by individuals or small teams, rarely emphasizes security. This study instead focuses on the practical and organizational conditions that lie between these extremes. These include the need for clear strategic direction, operational guidance, and internal support structures such as AI superusers. By shifting attention toward these enabling factors, the study highlights how AI can be responsibly and effectively integrated into infrastructure projects, beyond merely addressing technical security concerns.

V. Conclusions and Further Research

This study has explored the potential of Artificial Intelligence (AI) as a support for organizations engaged in large-scale infrastructure projects, with a particular focus on systems engineering roles. Three research questions guided the investigation:

(i) How can AI-based tools improve the management of system information in infrastructure projects?

(ii) In what ways can AI assist in core Systems Engineering tasks (such as handling requirements, standards, and project documentation)

(iii) What are the limitations and practical challenges of applying AI in real project settings?

The findings indicate that AI has the potential to significantly aid in managing complex system information, particularly in structuring, summarizing, and interpreting large volumes of textual data. Interview and case study evidence suggest that AI tools can support early-phase systems engineering activities by identifying requirements, tracking document changes, and surfacing assumptions. However, concerns about trust in AI-generated content were common among users. Given that Systems Engineering depends on traceability and accountability, the lack of transparency in AI outputs remains a key barrier. Currently, AI-assisted processes must be closely monitored and verified by human experts, which limits potential efficiency gains.

Furthermore, awareness of the organization's AI initiatives was found to be low, and perceived usefulness varied depending on task familiarity, user prompting skills, and access to internal data. Secure access to relevant documentation and well-formulated prompts were identified as critical enablers of AI utility.

The integration of AI into the broader sociotechnical system remains underdeveloped. While informal use of AI is increasing, its structural incorporation into existing workflows is lacking. Organizational change, rather than solely technical deployment, is necessary to realize the benefits of AI fully.

A key limitation identified was the inability to process confidential documents, which restricts many high-value use cases. The interviews found that the lack of knowledge regarding the project's security level was often a limiting factor, and projects that did have restricted or secret elements often had fewer concerns since it was well defined what parts of the project were restricted or not. Several participants emphasized the need for secure, internal AI systems tailored to organizational needs. Nonetheless, some tasks, particularly those that are repetitive and text-heavy, are already suitable for AI implementation. Summarizing lengthy documents, comparing versions, and drafting initial text are low-risk, high-impact areas where AI has demonstrated immediate value. Specifically, tools employing RAG approaches, such as NotebookLM, appear to offer a promising pathway to balance generative capabilities with verifiable source references. This combination may be especially suited for Systems Engineering contexts where traceability is critical. However, further empirical studies are needed to systematically evaluate whether RAG-based tools consistently outperform other generative systems in accuracy, user trust, and integration into workflows.

To support the effective adoption of AI in infrastructure projects, the following organizational actions are recommended:

- Strategic alignment: Develop a high-level strategy from management that outlines the intended role of AI across the organization, without prescribing specific tools or activities.
- Operational guidance: Provide clear guidelines on AI use, including recommended tools, data security protocols, and prompting techniques. Tools employing RAG approaches, such as NotebookLM, would be a good alternative for the organization to start with as it's transparent and therefore experienced as more trustworthy.
- Dedicated support roles: Assign AI superusers who possess both technical competence and contextual understanding of organizational processes.
- Experience sharing: Establish mechanisms for structured documentation and feedback from pilot activities to support organizational learning and iterative improvement.

Further action research in close collaboration with industry actors is recommended. Such research can provide deeper insights into how AI tools can be effectively leveraged to enhance Systems Engineering practices in large-scale infrastructure projects.

VI. Statement of Contribution

This study contributes new insights into the emerging role of AI as a support tool for Systems Engineering in large-scale infrastructure projects. By combining interviews, a survey, and pilot studies, it identifies both organizational challenges and practical enablers for AI adoption, offering actionable recommendations for integrating AI into existing sociotechnical systems and early-phase engineering practices.

ACKNOWLEDGMENT

This article is part of a broader PhD research project focused on managing complexity in railway infrastructure projects through the application of Systems Engineering. Some of the empirical results presented are based on data collected in two master's theses conducted within the scope of this research: *Optimizing Project Management in Large-Scale Railway Projects: A Study on the Integration of AI and Lean at Trafikverket* by Blessing Osamwanze and Rim El-Haj, and *Research and Development of Data Science and AI Tools for Project Management at Trafikverket* by Franz Erik Weijmer. The research was funded by the Swedish Transport Administration. This work was also supported by Formas – a Swedish Research Council for Sustainable Development, under grant decision number 2024-00087.

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