
AI-assisted Technology Roadmapping: Using LLM to Leverage Experts' Contributions

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Abstract: This study proposes an AI-assisted roadmapping approach that uses large language models (LLMs) to integrate data-driven and expert-based processes. Using a design science research methodology, three sequential industrial case studies were conducted to develop, test, and refine the proposed approach. The process comprises five stages: planning, roadmap definition, AI-assisted data collection, expert review, and strategy formulation. Results indicate that LLMs can effectively pre-populate roadmaps with diverse and

contextually relevant information, significantly reducing the time and effort experts spend on initial data collection. This shift allows experts to concentrate on higher-value activities such as validation, analysis, and decision-making. The findings also highlight the importance of carefully defining roadmap architecture and contextual inputs to ensure output quality.

Keywords: Technology Roadmapping (TRM); Artificial Intelligence (AI); Large Language Models (LLMs); Data-Driven; Expert-based; Design Science Research (DSR); Case Studies, Roadmap Architecture.

1 Introduction

Technology roadmapping (TRM) is a widely adopted management approach that supports the development of strategic plans for technology and innovation (Phaal *et al.*, 2004). Although it has been extensively studied, research on technology-assisted roadmapping remains limited (Kim *et al.*, 2025; Serrano *et al.*, 2024). Most roadmapping approaches are expert-based and rely on human judgment, which can be influenced by personal biases and constraints in knowledge processing and retrieval (Nazarenko *et al.*, 2022). Moreover, developing roadmapping workshops with domain expert attendance is often expensive and time-consuming, increasing required investments and making them inaccessible to many organisations (Oliveira, Freitas, *et al.*, 2022)

Although roadmapping has embraced data- and expert-driven approaches from the outset, expert-driven approaches have been predominant (Park *et al.*, 2020). In the last decade, a new era of data, coupled with the rise of artificial intelligence, has created new opportunities to explore the application of digital and data-driven technologies in roadmapping (Kim *et al.*, 2025; Pora *et al.*, 2022).

Roadmapping workshops, which have traditionally been conducted with analogue tools such as paper, pen, and sticky notes, have been affected by digital technologies. In recent years, influenced by the COVID-19 pandemic, digital technologies such as digital whiteboards, interactive displays, and virtual conference meetings have emerged as alternatives for conducting workshops while still maintaining an expert-driven approach (Oliveira, Routley, *et al.*, 2022). Although this shift towards digital roadmapping can influence process design, performance, and results, advantages such as the integration of experts from different locations and advanced information processing can be critical for some organisations and help overcome other limitations (Oliveira *et al.*, 2023).

This study explores whether applying artificial intelligence, specifically Large Language Models (LLMs), can help experts with roadmapping. During the training of LLM-based AI tools (e.g., ChatGPT and Gemini), large volumes of multidisciplinary data are used and can later be leveraged by users for specific purposes (AlKhamissi *et al.*, 2022; Petroni *et al.*, 2019). This study explores the existing data embedded in these tools to populate strategic roadmaps. It proposes a new process that merges expert and data-driven roadmapping into a new AI-assisted approach, reducing the time and effort required to collect and process roadmap data. As a result, experts' efforts in roadmapping workshops are mostly shifted from data generation to data analysis and strategic formulation.

The next section describes the research method. Then, the proposed AI-assisted approach is described, followed by an analysis of its capabilities based on the case

studies. Finally, conclusions are presented regarding the AI -assisted approach's contribution to theory and practice.

2 Research Method

This research conducted three case studies, following the design science research approach (Hevner *et al.*, 2004; Van Aken, 2005; Voss *et al.*, 2002), to develop, test, and refine the AI-assisted roadmapping proposal. The case studies were conducted sequentially, allowing feedback and insights from each case to improve the next, as proposed in design science research.

The first case study addressed business models for connected cars. 6 professionals from the automotive industry were involved in proposing a strategic roadmap to drive progress in the connected cars industry. The second case study involved an automotive supplier seeking product development opportunities in a particular technology line. Two professionals with relevant experience in managing projects related to this technology participated in the roadmap development. The third case study was conducted with the support of a machinery manufacturer that wanted to start a new product line not yet addressed by the current business units. Four professionals were involved in this case, including the CTO, the engineering manager, the project coordinator, and the mechanical designer.

The LLM provider used for the case studies was tested and selected as part of the first case study. Three providers were considered: ChatGPT 4o (OpenAI), Claude 3.5 Sonnet (Anthropic) and Gemini 1.5 Pro (Google). The research project considered the initial paid subscription for each one of them and replicated the same prompt. The collected results were presented and reviewed, with consideration of data clarity and variety. ChatGPT delivered the best results, according to the research team and experts, and was adopted for case 1 and subsequent cases.

All case studies used the Miro whiteboard tool to digitally organise and manage information generated throughout the roadmapping process. The roadmapping team comprised the main researcher, an assistant, and the case study participants. The main researcher is an academic and consulting expert in roadmapping, with expertise in artificial intelligence. The case participants were always experts in the subject of interest for roadmapping. Meetings among the roadmapping team (researchers and participants) were held both remotely and in person, depending on their availability and distance. Each AI-assisted roadmapping stage was conducted in separate meetings or workshops lasting 1 to 3 hours, fostering rapid, agile interactions among researchers and participants.

Case study data was collected through recordings, annotations and feedback forms. The research assistant was assigned to the data collection and structuring aligned with the roadmapping features and performance measures (Oliveira *et al.*, 2023). At the end of each case study, the research team analysed the stages of the AI-assisted approach using the collected data to identify points for improvement in the proposed artefact. These improvement points were implemented between the case studies, which were conducted sequentially, allowing the artefact to progress and reach a final contribution that fulfils the research problem and goals.

4 The AI-assisted Roadmapping Approach

The AI-assisted roadmapping approach comprises five stages, as shown in Figure 1: planning, roadmap definition, AI-assisted data collection, expert review, and strategy formulation. These stages follow a strategic roadmapping process adapted from Phaal et al. (2007).

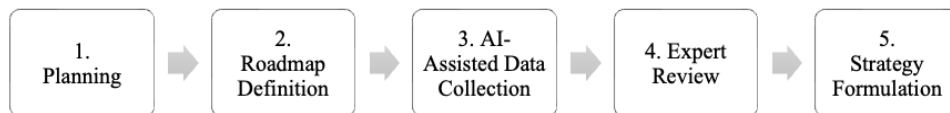


Figure 1 AI-assisted Roadmapping Stages

4.1 Planning

The “roadmapping planning” stage defines the motivation for conducting the roadmapping effort, the expected outcomes, the unit of analysis, and the working method. At this stage, a reduced team comprising the key stakeholders – the owner, sponsors, and facilitators – is assembled to drive roadmapping. This stage remains similar to traditional roadmapping processes, despite the potential adoption of digital technologies to support execution, such as digital whiteboards and videoconferencing.

4.2 Roadmap Definition

At the “roadmap definition” stage, the roadmapping team first needs to identify a set of digital documents that provide context for the unit of analysis. In the case studies developed in this research, a set of public documents, including research papers, industrial reports, technical standards, product catalogues, and market reports, provided the required results. With the context in place, the LLM tool can better understand the vocabulary related to the unit of analysis and better search the database for the requested information. The insertion of these documents to set the context is based on the RAG (Retrieval-Augmented Generation) technique, which LLM tools use to improve data retrieval and reduce hallucinations (Tural *et al.*, 2024).

Following this, the team begins building the roadmap architecture, comprised of layers and sublayers that serve as information categories for collection. The team can either use the LLM to help define the categories or mix business-predefined categories with LLM-suggested ones. The number of categories considered affects the number of notes generated and, thus, drives the scope and complexity of the roadmap. Prompt engineering best practices are adopted to improve data collection results (Liu *et al.*, 2026; Sahoo *et al.*, 2025). The roadmap architecture works as a guide for the next stage.

4.3 AI-assisted data collection

The “AI-assisted data collection” stage follows the roadmap architecture and uses the chosen LLM to generate a specified number of notes for each category-period

combination. Roadmap layers are executed separately, and notes are requested as brief descriptions to facilitate understanding. The goal is to provide an idea regarding the unit of analysis and the related category-period.

This stage is developed and reviewed by the roadmapping team. If the notes generated reflect the roadmapping goals in terms of the unit of analysis, business interests, and timeframe, the team exports them as a structured list to create a preliminary roadmap. If the team misses information or notices errors, the previous stages can be reviewed for selected documents, prompt design, categories and the LLM provider.

4.4 Expert Review

The “Expert review” stage analyses the preliminary roadmap to assess the information presented and ensure its business fit. In this sense, the experts selected by the roadmapping team attend a workshop to review and discuss each note. They can be grouped by speciality and roadmap layer to improve discussion and alignment.

Additionally, it is recommended to follow a structured approach when reviewing the notes. The following criteria: duplication, clarity, feasibility, roadmap position, and novelty, are employed in this order to help experts assess the notes. Duplication, clarity, and feasibility initially confirm the quality of the LLM-generated information from different perspectives. Notes passing this first threshold have the roadmap position (layers and timeframe) confirmed and receive a novelty classification. Once the entire roadmap is annotated, it is ready for the next stage.

4.5 Strategy Formulation

The “Strategy Formulation” stage addresses the annotations to create the final roadmap, which is then used to develop strategic actions. During this stage, participants can supplement the roadmap with new information as required to align with business interests and to fill in any gaps. Following it, as with other roadmapping processes, the roadmap and strategic actions must be communicated and deployed within the organisation.

5 Analysis of The Case Studies

The following sections provide an overview of the feedback, refinements, and insights gathered through the three case studies conducted during the development of the AI-assisted roadmapping approach. The “planning” and “strategy formulation” stages follow traditional roadmapping processes and are therefore not included in the analysis, which focused on the stages: roadmap definition, AI-assisted data collection, and expert review.

5.1 Roadmap Definition

This stage emphasises the roadmap architecture as a means of driving LLM data collection for the unit of analysis. It is critical because it will show the information categories considered relevant for the roadmap. Moreover, it allows merging the AI-suggested categories with those of business interest before collecting data.

The first case study provided relevant insights regarding the definition of the roadmap categories. It highlighted the importance of considering the number of categories requested from the LLM and the impact on the roadmap size in the next stage. As categories began to address similar topics, the team was warned to reduce the number of categories to avoid notes overlapping. Figure 2 shows the overloaded roadmap generated in case 1 due to the extended number of notes and categories that each expert had to address.



Figure 2 Overloaded roadmap caused by the extended number of notes and categories that each expert had to address

In the second and third case studies, the teams asked to mix LLM-suggested categories with those already in use in the business. This approach was insightful, as it improved the integration of current business lines with the AI-assisted approach, helping the teams to further align the roadmap results with current strategies.

In all three cases, the information categories proposed were accepted and adopted. Using LLMs helped teams design a roadmap architecture customised to the unit of analysis, rather than starting from a generic template (market, product, and technology) as is often recommended when organisations begin roadmapping (Phaal *et al.*, 2004). This can be a significant advantage, ensuring that critical information categories are addressed, even without involving a large group of experts.

5.2 AI-assisted Data Collection

In the first and second case studies, the researchers were still testing and learning to use the LLM's capabilities and to set up the best prompt. Thus, several adjustments were made to the note number, note template, and prompt design to guide the LLM through note generation and exportation. The third case study reached a stable proposal, and the researchers only adapted the prompt to align with the new unit of analysis.

Although the participants do not need to be involved in this stage, the researchers shared the results with at least the roadmapping owner before the expert review stage to manage expectations. The results for the categories and notes improved substantially across the three case studies as learnings were introduced into the process. Despite this,

all case studies yielded well-suited preliminary roadmaps. Figure 3 presents the roadmap created in case 2, in which participants were satisfied with the data collection results.

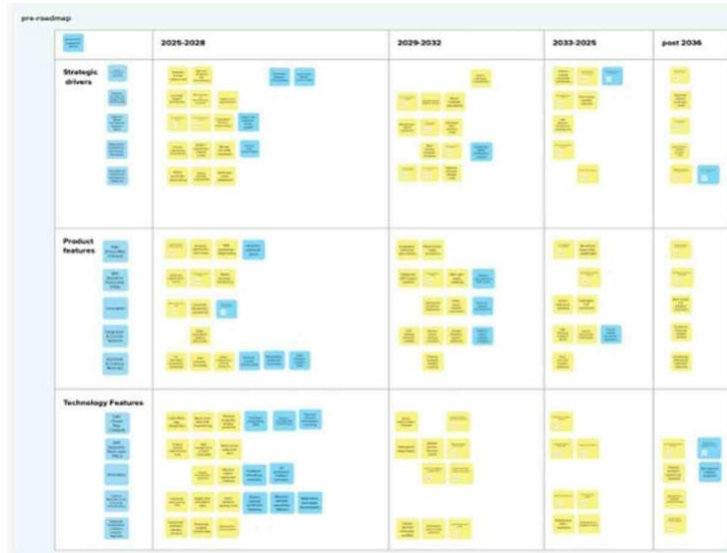


Figure 3 Preliminary roadmap used in case 2

5.3 Expert Review

In the first case study, the researchers opted to print the roadmap on A3 paper and hand it to the 6 participants during a three-hour in-person workshop. The first half of the workshop analysed and reviewed the roadmapping, and the second half focused on discussing the results and proposing strategic actions. During the first half, which represented the review stage, the participants were asked to identify duplicate, unclear, or infeasible notes to remove from the roadmap. All participants reviewed the entire roadmap, which comprised 380 notes, and suggested removing 33% of them. This case underscored for the researchers the importance of ensuring an appropriate amount of information to reduce the rejection rate. In addition, the review process required improvements to enhance understanding of the approved notes.

The second case study addressed the amount of information from the start, guiding the participants to focus on relevant categories and to control the number of notes. In addition, researchers adopted a digital approach, asking participants to review the roadmap directly on the Miro board. The review considered rejected notes for duplication, clarity, and feasibility, and among the approved notes, they were marked as needing repositioning and as novel ideas. A presential 2-hour workshop was conducted with the researcher and two experts. From the 135 notes generated, 10% were rejected, 90% approved, 17% repositioned, and 18% considered novel. The results and participants' feedback were substantially positive. During the review process, the researchers noticed that note generation could still be improved in terms of word length to better balance understanding and reading effort.

The third case study followed the AI-assisted approach used in the second case study, with minor adjustments to note length. In this case, 6 participants attended a virtual workshop using a shared Miro board. The workshop lasted 2,5 hours and reviewed 280 ideas. The participants formed three 2-person groups aligned to their expertise to review each roadmap layer separately. As a result, 13% of the total were rejected, 87% were approved, 23% were repositioned, and 30% were considered novel. Results and participants' feedback remained significantly positive in this case, with no relevant process-improvement points identified by the researchers.

Figure 4 shows the roadmap created in case 3, annotated after the expert review. Despite the large number of notes and categories, this roadmap was a design choice by the roadmapping team, who deliberately extended the categories to merge AI-recommended and business categories. In addition, this roadmapping team included more experts, allowing the roadmap sections to be handled concurrently by different groups.

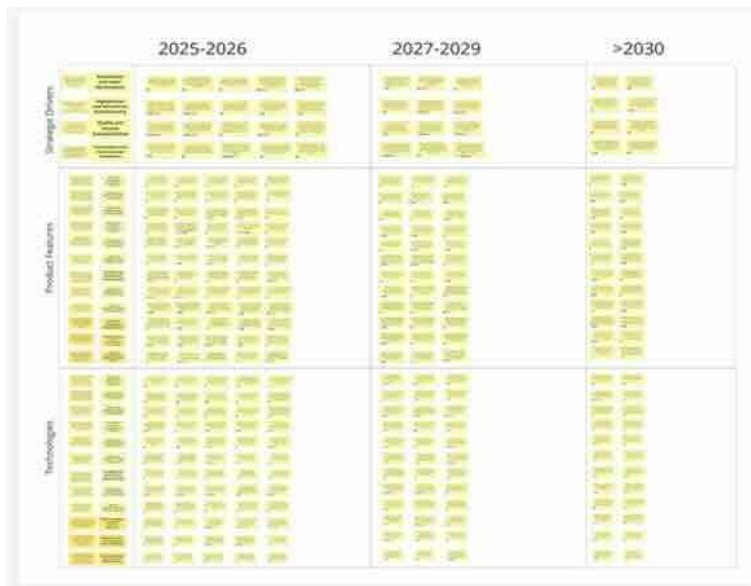


Figure 4 Roadmap after expert review in case 3

6 Conclusions

This study proposed and tested an AI-assisted roadmapping approach that uses LLMs to pre-populate strategic roadmaps and optimise experts' participation. Overall, the results from the case studies indicate that the proposed approach is feasible and promising. The preliminary roadmaps generated through the AI-assisted approach provided sufficient volume and breadth of information to support strategic discussions, while enabling experts to focus on reviewing, validating, and refining the roadmap content rather than spending most of their time on data collection.

The contribution to the roadmapping literature lies in advancing the discussion of digitalisation in roadmapping. It proposes a structured approach that integrates an LLM

to collect and process roadmap data. The study also highlights the importance of clearly defining roadmap architecture, since it directly guides data collection and influences the roadmap's analytical usefulness. In addition, the AI-assisted roadmapping presented in this research explores the advantages of expert and data-driven approaches and proposes a novel one. Currently, these approaches tend to remain disconnected, with few integration attempts in the literature (Nazarenko et al., 2022). This study highlights opportunities to use LLMs as enablers for this integration.

The contribution to practice lies in the potential reduction in the time and effort required of experts during the initial stages of roadmap creation. Thus, the proposed approach may benefit organisations with limited access to experts, such as small and medium-sized organisations, by enabling a faster start to roadmap development and allowing expert effort to be invested in strategic activities rather than in data collection.

Despite the positive results, this research presents limitations. First, the study was conducted through only three case studies, limiting generalisation. Second, the approach was applied in a controlled setting and supported by researchers with roadmapping and AI competencies, which may hinder the adoption by less-experienced teams. Third, the approach relies on prompt engineering and RAG techniques for LLM applications, which can introduce significant variations and affect data collection.

Future work can incorporate comparative evaluations of AI-assisted and traditional roadmapping and explore further hybrid approaches that combine data-driven and expert-based roadmapping.

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