Uso de asistentes LLM como soporte en el proceso de Formulación de Proyectos: Un mapeo sistemático

Use of LLM assistants as support in the Project's Formulation process: A Systematic Mapping

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Artículo de Investigación Científica

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Resumen

Introducción: La formulación de proyectos exige definir objetivos, alternativas, recursos y criterios de evaluación en contextos cada vez más complejos. En Colombia, pese al respaldo de la Metodología General Ajustada (MGA), persisten barreras técnicas y operativas. La Inteligencia Artificial Generativa, en particular los modelos de lenguaje grandes (LLM, por sus siglas en inglés), aparece como apoyo para redacción, síntesis y planeación, pero su adopción en formulación aún carece de evidencia consolidada

Objetivo: Identificar y clasificar cómo se han aplicado los LLM en la formulación de proyectos, sus beneficios y limitaciones, los métodos de evaluación usados, los ámbitos de aplicación y la existencia de herramientas LLM o GenAI que apoyen la MGA.

Metodología: Mapeo sistemático siguiendo a Petersen. Se definieron preguntas con PICOC, cadenas de búsqueda y criterios de inclusión y exclusión. Se consultaron IEEE Xplore, Scopus, ScienceDirect, Web of Science y Taylor & Francis entre 2020 y 2025. El diagrama PRISMA resumió identificación, cribado y selección. Del total de 372 registros, 33 estudios cumplieron los criterios.

Resultados: Predominan modelos GPT-3.5 y GPT-4. Las tareas con mayor evidencia incluyen estimación de esfuerzo y tiempo, generación de planes y cronogramas, ideación y diseño, y gestión temprana de riesgos. También se observó apoyo a requisitos, desglose del trabajo y asignación de recursos. La evaluación combinó comparaciones con humanos, revisión experta, métricas automáticas con otros LLM, encuestas o entrevistas y medidas objetivas. No se hallaron reportes de herramientas LLM o GenAI para apoyar la MGA.

Conclusiones: Los LLM aceleran tareas cognitivas y mejoran claridad y creatividad, pero requieren validación humana, mejor contextualización, explicabilidad, resguardo de datos e integración técnica. Se observan tendencias hacia enfoques híbridos con RAG, agentes multitarea y capacidades multimodales. La ausencia de experiencias para MGA revela una oportunidad estratégica de investigación y desarrollo.

Palabras clave: LLM; inteligencia artificial generativa; formulación de proyectos; definición de proyectos; asistencia.

Abstract

Introduction: Project formulation requires defining objectives, alternatives, resources, and evaluation criteria in increasingly complex contexts. In Colombia, despite the support of the Adjusted General Methodology (MGA), technical and operational barriers persist. Generative Artificial Intelligence, particularly large language models (LLMs), has emerged to support writing, synthesis, and planning, but its use in project formulation still lacks consolidated evidence.

Objective: To identify and classify how LLMs have been applied to project formulation, their benefits and limitations, the evaluation methods used, application domains, and the existence of LLM or GenAI tools that support the MGA.

Method: Systematic mapping following Petersen. Research questions were defined with PICOC, together with search strings and inclusion and exclusion criteria. IEEE Xplore, Scopus, ScienceDirect, Web of Science, and Taylor & Francis were queried from 2020 to 2025. A PRISMA diagram summarized identification, screening, and selection. Of 372 records, 33 studies met the criteria.

Results: GPT-3.5 and GPT-4 predominate. The most evidenced tasks include effort and time estimation, plan and schedule generation, ideation and design, and early risk management. Support was also observed for requirements, work breakdown, and resource allocation. Evaluation combined human comparisons, expert review, automatic metrics with other LLMs, surveys or interviews, and objective measures. No reports were found of LLM or GenAI tools to support the MGA.

Conclusions: LLMs speed up cognitive tasks and improve clarity and creativity, but they require human validation, better contextualization, explainability, data protection, and technical integration. Trends point to hybrid approaches with retrieval augmented generation (RAG), multitask agents, and multimodal capabilities. The absence of reported experiences for the MGA reveals a strategic opportunity for research and development.

Keywords: LLM; generative artificial intelligence; project formulation; project definition; assistance.

INTRODUCTION

The formulation of projects consists of identifying, structuring, and organizing a set of interrelated activities aimed at solving a problem or need by defining objectives, strategies, resources, costs, methodology, schedule, and evaluation criteria, among others, in order to ensure the technical, economic, social, environmental, and financial feasibility of a project prior to its execution. This phase is essential for maximizing the likelihood of success, as a robust definition makes it possible to anticipate risks, optimize resources, and establish appropriate monitoring indicators [1] [2].

It has been shown that proper formulation does not by itself guarantee a project's success, since execution faces multiple challenges due to increasingly complex contexts, rapidly changing environments, and diverse, voluminous information, all of which hinder timely and sound decision-making. Moreover, in some organizations there is limited technical capacity and frequent staff turnover, making it difficult to preserve knowledge and experience [3] [4].

During the project formulation and design stage, key challenges arise, such as precisely defining objectives and interdependent solutions that evolve with the context, which demands iterative and adaptive approaches to clarify those objectives and design alternatives [1]. During the project formulation and design stage, key challenges arise, such as precisely defining objectives and interdependent solutions that evolve with the context, which demands iterative and adaptive approaches to clarify those objectives and design alternatives [3]. Added to this is high technological and market uncertainty, which leads to frequent changes in scope and demand, and the lack of robust risk management systems to mitigate schedule and cost deviations [4]. Finally, in distributed-team settings, cultural barriers and geographic dispersion further complicate coordination and information flow, raising the likelihood of misunderstandings and operational delays.

In Colombia, as a response to these challenges, the Adjusted General Methodology (Metodología General Ajustada, MGA) has been adopted as the official tool for designing, monitoring, and evaluating public investment projects under the direction of the National Planning Department (Departamento Nacional de Planeación, DNP). The purpose of this methodology is to ensure that resources are allocated efficiently, effectively, and appropriately through an orderly process that includes the stages known as Profile, Formulation, Evaluation, and Final Formulation, based on standardized criteria of cost–benefit analysis and results-based management [5] [6] [7].

Despite the strong regulatory backing of the MGA, its application faces several technical and institutional difficulties that affect the quality and timeliness of projects. Chief among these are: the lack of specialized training in areas such as the logical framework, cost–benefit evaluation, and sector-specific regulations, which forces reliance on external consultants and widens regional disparities in access to public resources [8] [9] [10]; and the use of the MGA Web platform, whose rigid formats and inflexible tools (macros and templates) hinder the updating, manipulation, and printing of documents especially when staff changes occur. Notwithstanding the existence of the platform, manual, paper-based formulation processes persist, forcing task duplication by requiring retyping of the project, with the attendant risk of data-entry errors that increase administrative costs [8]. These difficulties are even more critical in low-income municipalities, where limited institutional and administrative capacity prevents adequate project formulation, significantly reducing their chances of accessing funds from the General System of Royalties and thereby perpetuating the territorial inequalities the MGA seeks to overcome [11]. Taken together, these obstacles highlight the need to strengthen capacities, simplify tools, and adapt the methodology to territorial contexts.

In this setting, Generative Artificial Intelligence (GenAI) and, in particular, large language models (LLMs) can assist in drafting documents, structuring objectives, synthesizing information, and generating coherent decision scenarios [12] [13] [14]. These capabilities enable project teams to accelerate complex cognitive tasks, standardize processes, and improve the quality of proposals.

Nevertheless, the adoption of LLMs in project formulation is still incipient and lacks consolidated evidence regarding their effectiveness and limitations. It is therefore essential to conduct a systematic mapping of the available scientific literature to identify the state of the art, main findings, research gaps, and future trends at the intersection of GenAI or LLMs and the project formulation process [15], [16].

With this aim, the article is structured into three essential sections: Methodology (Section 2), which details how the objective and research questions were defined, the search strategy, inclusion and exclusion criteria, and the study selection process; Results (Section 3), which summarizes the findings, including the number of studies included and their main characteristics; and Answers to the research questions (Section 4), which presents responses to each of the five research questions defined during the planning phase, based on the selected studies. Finally, we present the conclusions and the future work the research group expects to undertake in the near term.

METODOLOGHY

The methodology employed to develop this systematic mapping was that proposed by Petersen et al. [17]. This methodology was selected for its rigorous and structured approach. It involved defining the following phases: planning, execution, and reporting, with the aim of ensuring reproducibility. Fig 1 the overall process followed in developing this systematic mapping [18].

In the planning phase, we first defined the objective of the mapping. With support from the PICOC technique, we then established the research questions, (five in total). Next, we defined the search strategy, which entailed specifying the search string and selecting the relevant academic sources. For the documents to be collected, we defined inclusion and exclusion criteria.

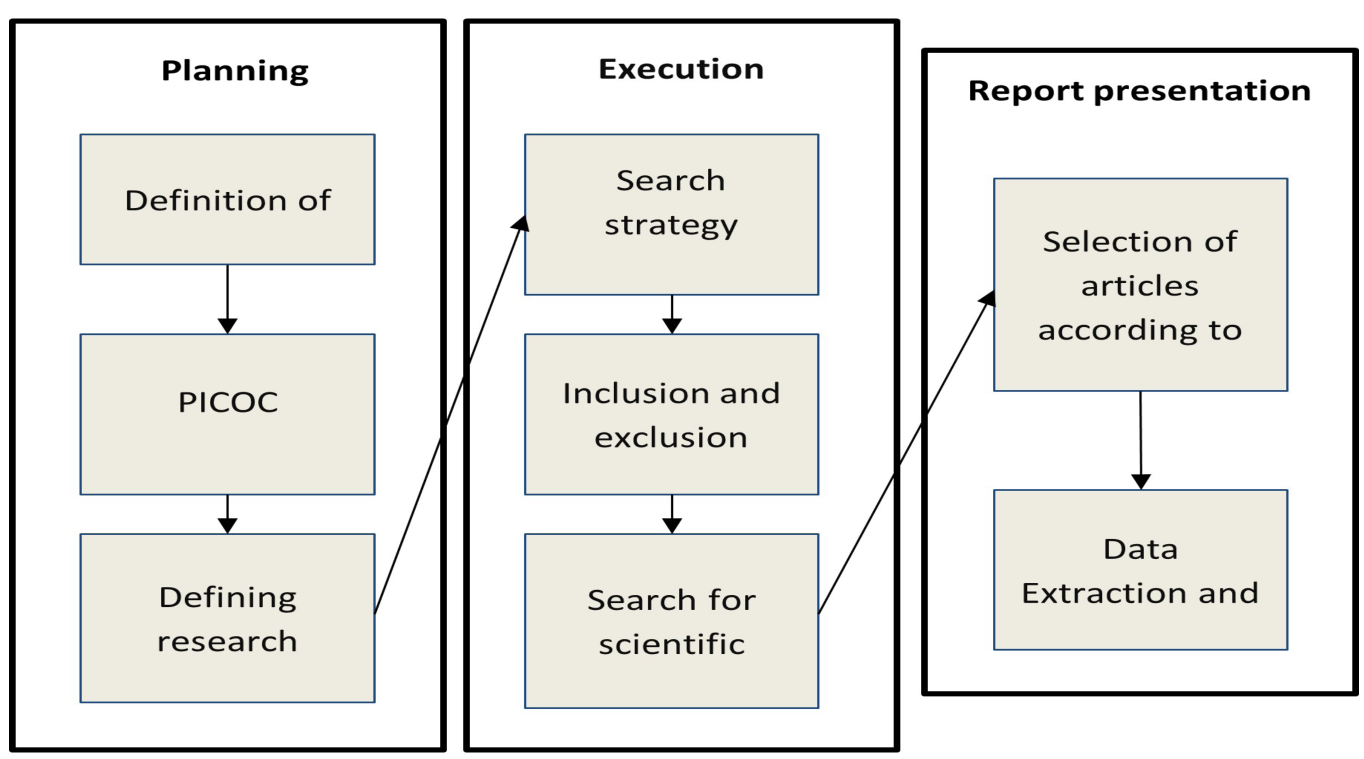

Fig 1. Selection methodology

Mapping planning

Definition of the research objective

Since Large Language Models (LLMs) have become established as key tools for optimizing complex processes, it is essential to thoroughly assess their applicability in project formulation. Therefore, we propose to analyze how LLMs have been incorporated into project formulation, their benefits and challenges, and the criteria used to measure their impact on efficiency and accuracy. In this regard, we seek to identify and classify the different LLMs applied to project formulation, describing their main characteristics and associated usage contexts.

PICOC to structure the research questions

The research questions were structured using the PICOC technique [19], as follows:

- **Population:** Large Language Models (LLMs).
- **Intervention:** LLM-based assistants applied to the formulation, planning, or definition of projects.
- **Comparison:** Traditional project formulation methods or non-AI expert systems, in order to contextualize the findings.

- **Outcome:** Advantages, disadvantages, challenges, trends, application areas, and evaluation methods identified in studies on LLMs in project formulation.
- **Context:** Different domains (engineering, health, education, project management, and others) and the methodological approaches used in each.

This PICOC scheme facilitated the development of the search strategy and the interpretation of the results.

Research questions

A key step for the success of the mapping is the formulation of the research questions, since these guide and delimit the search process and the achievement of the mapping objective. To this end, we conducted a state-of-the-art analysis on LLMs or GenAI applied to the project formulation process, in order to identify the most relevant works related to the selected topic. The research questions sought to include the why, the how, and the where of the research objective, as shown in Fig 2.

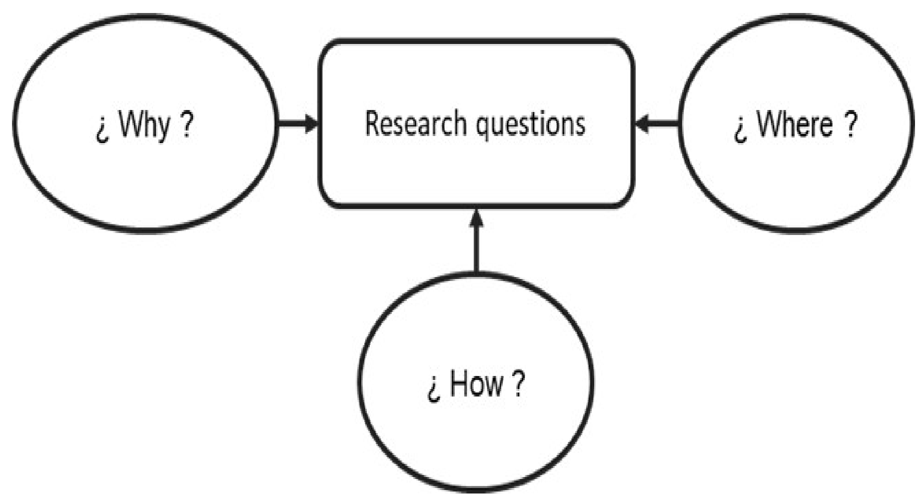

Fig 2. Guide to formulating research questions

Guide to formulating research questions

- **Why?** To establish a clear focus and bound the scope, serving as guidance for analyzing and selecting the studies reviewed.
- **How?** To properly center the chosen topic, recognizing key concepts, core content, and the different approaches addressed in the research.
- **Where?** To consider all identified studies related to the chosen topic.

Based on the preceding analysis, the research questions that will guide this study were formulated. Table 1 presents the General Question (GQ) and the Specific Questions (SQ), each accompanied by its corresponding rationale.

TABLE 1. RESEARCH QUESTIONS.

Indicator	Research Question	Rationale
GQ	Which LLMs have been applied to project formulation?	Identify the most relevant and widely used LLMs to establish a technological foundation in the study area.
SQ1	Which specific tasks within the project formulation process have been supported by LLMs?	Understand in which stages or activities of the formulation process LLMs provide the greatest value, efficiency, or automation.
SQ2	What advantages, disadvantages, challenges, and trends have been identified in implementing LLMs in this context?	Analyze the practical benefits and limitations of integrating LLMs, as well as emerging trends that guide their future use
SQ3	What methods have been used to evaluate the effectiveness of LLM-based assistants in project formulation?	Identify the criteria and methodologies that measure the real impact of LLMs on the quality and efficiency of the formulation process.
SQ4	In which contexts or areas of knowledge has the use of LLMs for project formulation been applied, and what methodological approaches have been used?	Determine the applicability of LLMs across domains and the methodological approaches that support their implementation in those contexts.

Indicator	Research Question	Rationale
SQ5	Which LLM- or GenAI-based tools have been developed or used to support the MGA in Colombia?	Identify concrete technological solutions that integrate LLMs or GenAI within the MGA framework, in order to gauge their degree of adoption, suitability to the Colombian context, and potential to automate the project formulation process.

Mapping execution

Search strategy and information sources

To identify relevant studies, the following academic databases were used: IEEE Xplore, ScienceDirect, Scopus, Web of Science, and Taylor & Francis. The search strings were built using a combination of key terms, including: "large language models," "generative AI," "project," "planning," "formulation," and "definition." The search string was:

(LLM OR "large language model" OR genai OR "generative Artificial intelligence" OR "generative AI") AND ("project") AND ("planning" OR "formulation" OR "definition")

Additionally, the following search string was used to retrieve articles related to the MGA and GenAI or LLM:

(LLM OR genai OR "generative AI" OR "Inteligencia Artificial Genetativa") AND ("Metodología General Ajustada")

Inclusion and Exclusion Criteria

To ensure the quality and relevance of the reviewed articles, the following inclusion and exclusion criteria were established, as shown in Table 2.

TABLE 2. INCLUSION AND EXCLUSION CRITERIA.

Inclusion Criteria	Exclusion Criteria
Studies on LLMs or Generative AI (GenAI) in project formulation.	Studies that only mention AI without applying it to project formulation.
Evaluation of the benefits and challenges of using LLMs in project planning.	Articles focused on general AI in management without an emphasis on formulation or planning.
Peer-reviewed journal articles in indexed venues.	Undergraduate or master's theses not published in indexed journals.
Conference proceedings on LLMs applied to project formulation.	Books, book chapters, or technical documents that are not peer-reviewed.
From 2020 to 2025 to ensure recency.	Publications prior to 2020.
English or Spanish to ensure comprehension.	Publications in other languages unless official accessible translations exist.
Full-text access to the scientific article.	No access to the article.

Report Presentation

Study Selection

The selection process was carried out in four stages;

1. Initial search: All studies that matched the search strings and fell within the search period (2020 to 2025) were retrieved.

2. Deduplication: Duplicate studies were removed, retaining only one version.

3. Title and abstract screening: Titles and abstracts were assessed to filter out articles that did not meet the inclusion criteria or that met the exclusion criteria.

4. Analysis of the selected studies: Based on the full text of the selected studies, we proceeded with reading and analysis to confirm their relevance and their contribution to at least one research question, supported by the PICOC technique.

Data extraction and Analysis

The data extracted from the articles were organized according to the research questions (LLM models, supported tasks, advantages and challenges, evaluation methods, and application contexts). A template was used to code key variables for each study: model name, types of tasks performed, reported benefits and limitations, metrics and indicators used, and sectors and methodologies employed. This enabled: a descriptive synthesis of the frequency of LLM use and the most common tasks they support; a qualitative thematic analysis of recurring advantages, challenges, and trends; a comparison of evaluation approaches and metrics to identify best practices and methodological gaps; and, finally, an application mapping that visually displays the domains and research methods most explored at the convergence of GenAI and project formulation.

RESULTS

As a result of the search process, a total of 372 studies were retrieved from the academic sources, and after screening, 33 were selected. The PRISMA diagram shown in. Fig 3 summarizes the stages of identification, screening, and final selection of the studies. The full review of the 33 selected articles confirmed their relevance for answering the research questions. As shown in the diagram, most documents (195) were retrieved from IEEE Xplore, followed by Scopus with 153, then ScienceDirect and Web of Science with 12, and finally Taylor & Francis with 1. In addition, studies were identified through other methods, from which 10 additional studies were incorporated, thereby strengthening the robustness and breadth of the systematic mapping.

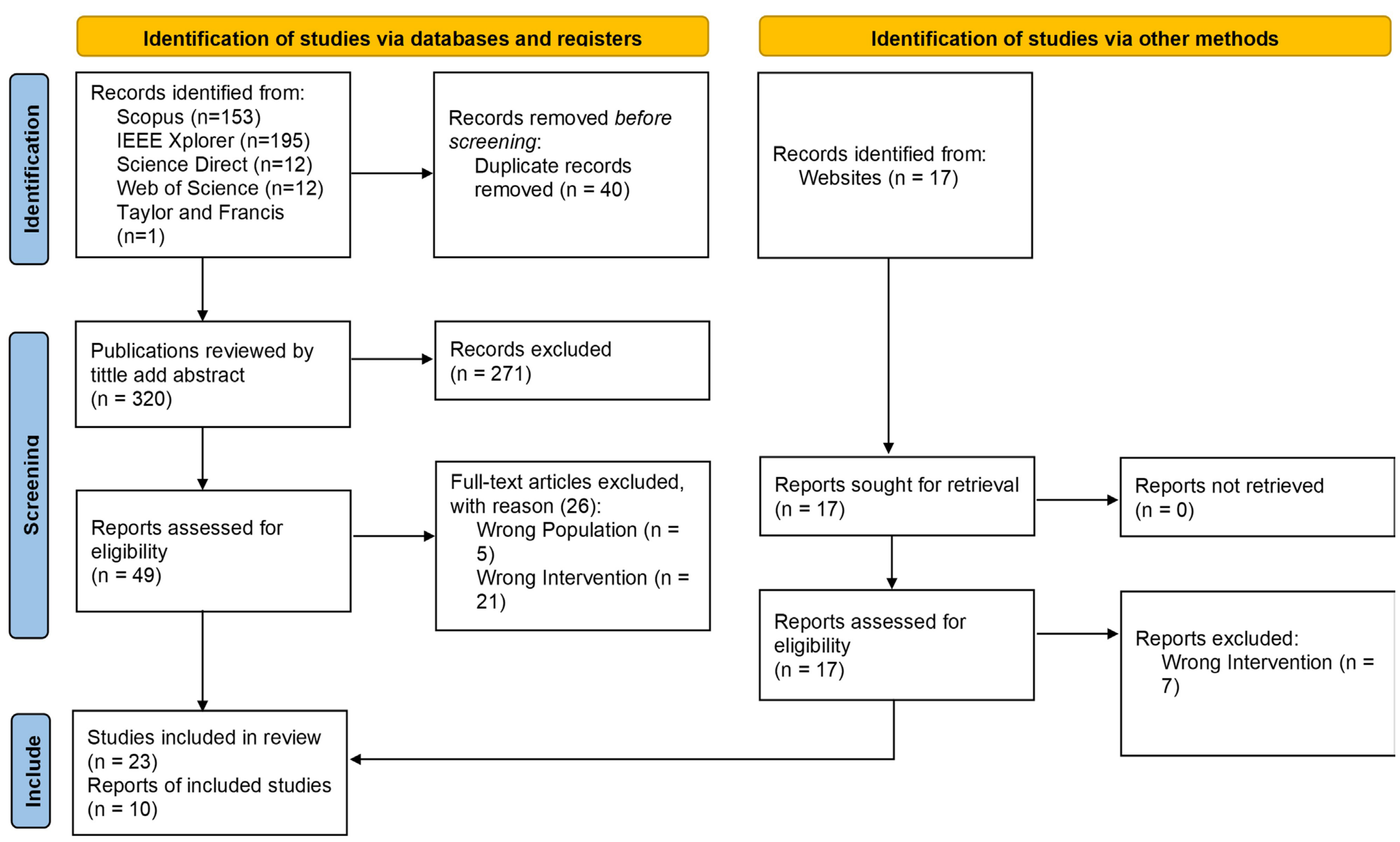

Fig 3. PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources

Table 3 presents the selected studies, organized by year of publication, which makes it possible to observe how LLMs have been applied in different contexts to support project formulation.

TABLE 3. SELECTED STUDIES (2023–2025).

Ref	Tittle	Authors	Year	General Description
[20]	Who is better in project planning? Generative artificial intelligence or project managers?	André Barcaui, André Monat	2023	Compares plans produced by GPT-4 with those of human managers, showing that the ideal approach is to combine both.
[21]	Putting Intellectual Robots to Work: Implementing Generative AI Tools in Project Management White Paper	Jiaxiong Weng	2023	Practical guide to using ChatGPT in project management aligned with PMI standards.

Ref	Tittle	Authors	Year	General Description
[22]	TPTU: Large Language Model-based AI Agents for Task Planning and Tool Usage	Jingqing Ruan, Yihong Chen, Bin Zhang, Zhiwei Xu, Tianpeng Bao, Guoqing Du, Shiwei Shi, Hangyu Mao, Ziyue Li, Xingyu Zeng, Rui Zhao	2023	System that tests how well different AIs plan complex tasks.
[23]	Innovative Approach to Agile Education: Generative AI-Supported Planning Poker Simulation	Khalid Naful, Youssef Lefdaoui	2023	Uses AI to simulate Planning Poker games in class, helping students estimate tasks.
[24]	Role of ChatGPT and Similar Generative Artificial Intelligence (AI) in Construction Industry	Nitin Liladhar Rane	2023	Uses of ChatGPT in construction, from design to on-site safety.
[25]	Integrating ChatGPT, Bard, and leading-edge generative artificial intelligence in architectural design and engineering: applications, framework, and challenges	Nitin Liladhar Rane, Saurabh P. Choudhary, Jayesh Rane	2023	Compares AI tools for architectural design and their practical integration.
[26]	GenAI Tools to Improve Data Science Project Outcomes	Akit Kumar, M.S. Lakshmi Devi, Jeffrey S. Saltz	2024	What data scientists need from AI tools to collaborate more effectively.
[27]	Integrating Generative AI for Advancing Agile Software Development and Mitigating Project Management Challenges	Anas Bahi, Jihane Gharib, Youssef Gahi	2024	Uses AI to improve agile project management (Scrum) by automating tasks and enhancing planning.
[28]	Large Language Model Employment for Story Point Estimation Problems in AGILE Development	Barkhah Permana, Ridi Ferdiana, Azkario Pratama	2024	AI that predicts task difficulty (story points) in agile development using models such as BERT.
[29]	Intelligent Q&A System for Mountainous Transmission Line Design Based on Vector Retrieval	Caiqian Wang, Jinya Zhou, Jiamin Chen	2024	AI-powered question-and-answer system for designing transmission lines in mountainous areas.
[30]	A Creative Methodological Approach for Planning Complex Technological Projects Using OTSM-TRIZ, DSM, CPM, and Generative AI	Christopher Nikulin, Cristobal Arrieta, Cristian Valdés, Manuel Mancilla, Paulina González	2024	Combines traditional methods with ChatGPT to solve complex problems in technological projects.
[31]	Utilizing Large Language Models to Illustrate Constraints for Construction Planning	Chuanni He, Bei Yu, Min Liu, Lu Guo, Li Tian, Jianfeng Huang	2024	AI that identifies and explains constraints in construction projects more effectively than traditional methods.
[32]	Empowering Diversity by Building Inclusive Software Engineering Projects with Large Language Models	Clara Maathuis, Greg Alpar, Stefano Bromuri	2024	AI that helps create inclusive educational software for children with dyslexia.
[33]	Agile Project Management Using Large Language Models	Dhruva G, Sapna V M, Ishaan Shettigar, Srikrshna Parthasarthy (PES University, India)	2024	How AI can help organize tasks and teams in agile software projects.
[34]	AI and the Future of Collaborative Work: Group Ideation with an LLM in a Virtual Canvas	Jessica He, Stephanie Houde, Gabriel Enrique Gonzalez, Dario Andres Silva Moran, Steven I. Ross, Michael Muller, Justin D. Weisz	2024	How AI can support group ideation using shared virtual whiteboards.
[35]	Software Development Automation Using Generative AI	K. R. Raghi, K. Sudha, Sreeram A. M., Steve Joshua S.	2024	AI generates code, performs tests, and documents automatically, accelerating software development.

Ref	Tittle	Authors	Year	General Description
[36]	Revolutionizing Project Collaborations: The Role of AI Integration	Malaika Monteiro, Ivan Dsilva, Sarah Abraham, Athsa Nadar, Prajakta Dhamanskar	2024	Platform that uses AI to organize work between students and companies.
[37]	An Autonomous Multi-Agent LLM Framework for Agile Software Development	Manish Sanwal, Ishan Deva	2024	System with multiple AIs working together to automatically develop software in an agile manner.
[38]	Artificial Intelligence-Based Solution Model for Real Estate Business and Entrepreneurial Operations	Nasser Abouzakhar	2024	ChatGPT as an intelligent assistant for real estate analysis and property design.
[39]	Potential Role and Challenges of ChatGPT and Similar Generative Artificial Intelligence in Architectural Engineering	Nitin Liladhar Rane	2024	How ChatGPT can assist in architecture and the potential issues involved.
[40]	The Artificial Intelligence Revolution in New-Product Development	Robert G. Cooper	2024	How tools such as ChatGPT and DALL·E are changing the way new products are created.
[41]	Enhancing Project Formulation in Engineering Education Through ChatGPT and Product Development Tools	Salvador Gonzalez-Garcia, Gerardo Loreto-Gómez, Jorge Rodríguez-Arce	2024	Students use ChatGPT alongside traditional methods to design projects.
[42]	LLM enabled generative collaborative design in a mixed reality environment	Shengyang Xu, Yao Wei, Pai Zheng, Jia Zhang, Chunyang Yu	2024	AI and mixed reality to improve teamwork among designers.
[43]	Can GPT-4 Aid in Detecting Ambiguities, Inconsistencies, and Incompleteness in Requirements Analysis? A Comprehensive Case Study	Taslim Mahbub, Dana Dghaym, Aadhith Shankarnarayanan, Taufiq Syed, Salsabeel Shapsough, Imran Zualkernan	2024	Assesses how well GPT-4 can find errors in software technical documents.
[44]	Effort Estimation in Agile Software Development - Is AI a Resourceful Addition?	Vasilka Saklamaeva, Luka Pavlič	2024	Tests an AI tool (GitLab Duo) for time estimation in agile projects.
[45]	Using Generative AI for a Graduate Level Capstone Course Design—a Case Study	Wei Lu, Behbood „Ben“ Ben Zoghi	2024	How ChatGPT helped design an advanced university engineering course.
[46]	LLM-based agents for automating the enhancement of user story quality: An early report	Zheying Zhang, Maruf Rayhan, Tomas Herda, Manuel Goisauf, Pekka Abrahamsson	2024	AI that automatically improves user story descriptions in agile development.
[47]	Generating textual explanations for scheduling systems leveraging the reasoning capabilities of large language models	Cheyenne Powell, Annalisa Riccardi	2025	AI that explains in plain language how scheduling systems plan tasks in factories or offices.
[48]	AgentGen: Enhancing Planning Abilities for Large Language Model based Agent via Environment and Task Generation	Mengkang Hu, Pu Zhao, Can Xu, Qingfeng Sun, Jianguang Lou, Qingwei Lin, Ping Luo, Saravan Rajmohan	2025	Trains AI with many different environments and tasks so it learns to plan better.
[49]	An Innovative Solution to Design Problems: Applying the Chain-of-Thought Technique to Integrate LLM-Based Agents With Concept Generation Methods	Shijun Ge, Yuanbo Sun, Yin Cui, Dapeng Wei	2025	AI that helps designers be more creative by using techniques such as brainstorming.

Ref	Tittle	Authors	Year	General Description
[50]	Enhancing participatory planning with ChatGPT-assisted planning support systems: a hypothetical case study in Seoul	Steven Jige Quan, Seojung Lee	2025	Platform with ChatGPT that helps citizens design urban proposals in Seoul through intelligent agents, improving public participation.
[51]	Knowledge augmented generalizer specializer: A framework for early stage design exploration	Vijayalaxmi Sahadevan, Rohin Joshi, Kane Borg, Vishal Singh, Abhishek Raj Singh, Bilal Muhammed, Sohan Babu Beemaraj, Amol Joshi	2025	AI that helps decompose complex problems in early-stage design using specialized knowledge.
[52]	Leveraging Generative AI Tools for Proactive Risk Mitigation in Design	Yunwei Hu, Amith Nag N A, David D. Yellamati, Yavuz Goktas (Schneider Electric)	2025	Three ways to use AI to prevent risks in engineering design.

Answers to research questions

GQ. Which LLM models have been applied in project formulation?

As shown in Fig 4, models from the GPT family stand out as the most widely used to support the project formulation process, with consistent presence over the years. Overall, an increase in their adoption is observed, especially in 2024, when generic GPT models and advanced versions such as GPT-3.5 and GPT-4 reached higher usage frequency. Meanwhile, models such as Bard, Claude, PaLM, and others appear less frequently, indicating that their application is less common compared to the main models.

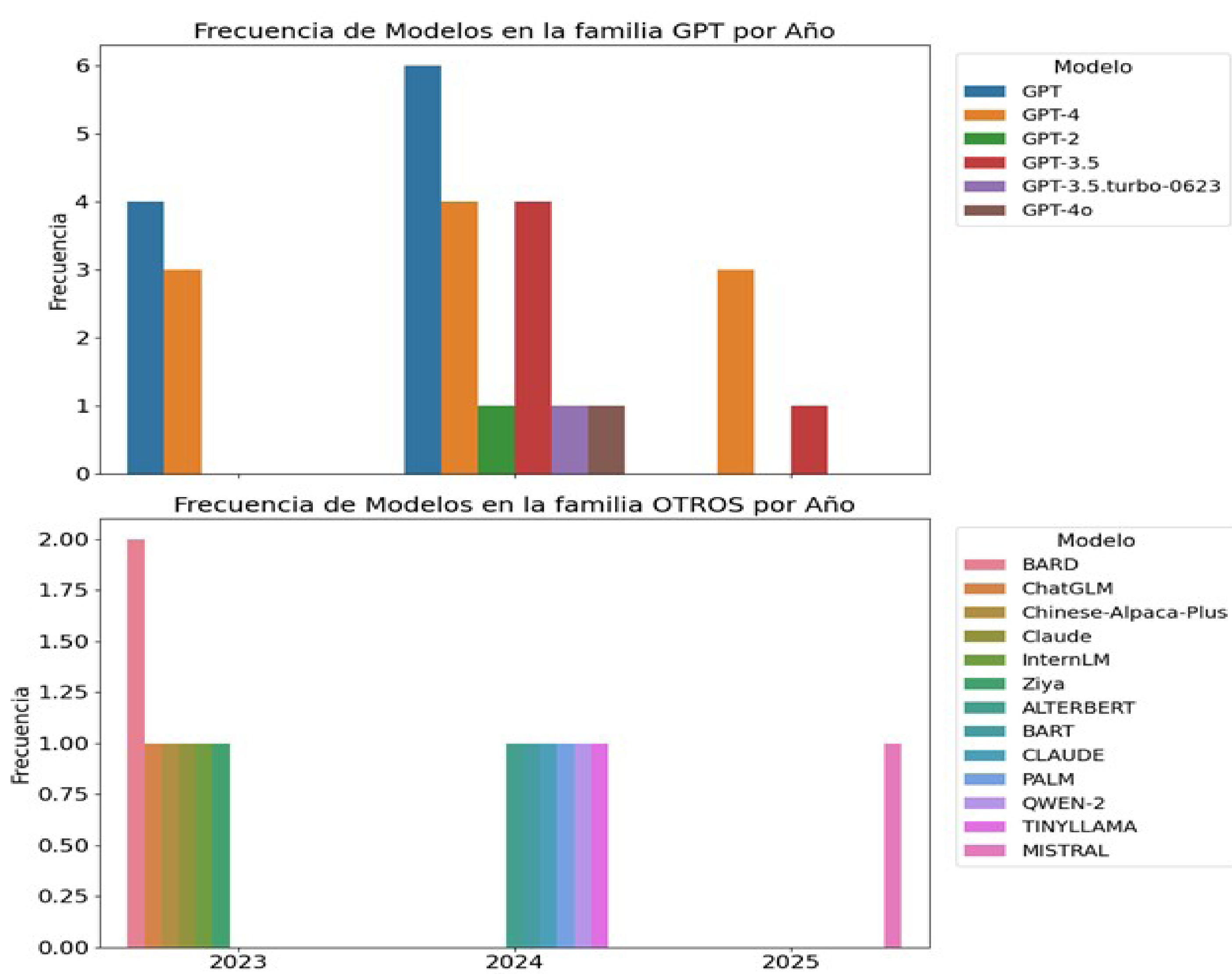

Fig 4. Frequency of use of LLM models between 2023 and 2025. (a) GPT family models and (b) Others

On the other hand, Fig 5 shows that models from the LlaMA and GEMINI families begin to be used in 2024 and 2025, suggesting a growing adoption of these technologies. In summary, GPT models remain predominant, but there is a rising trend toward diversification with the adoption of other models.

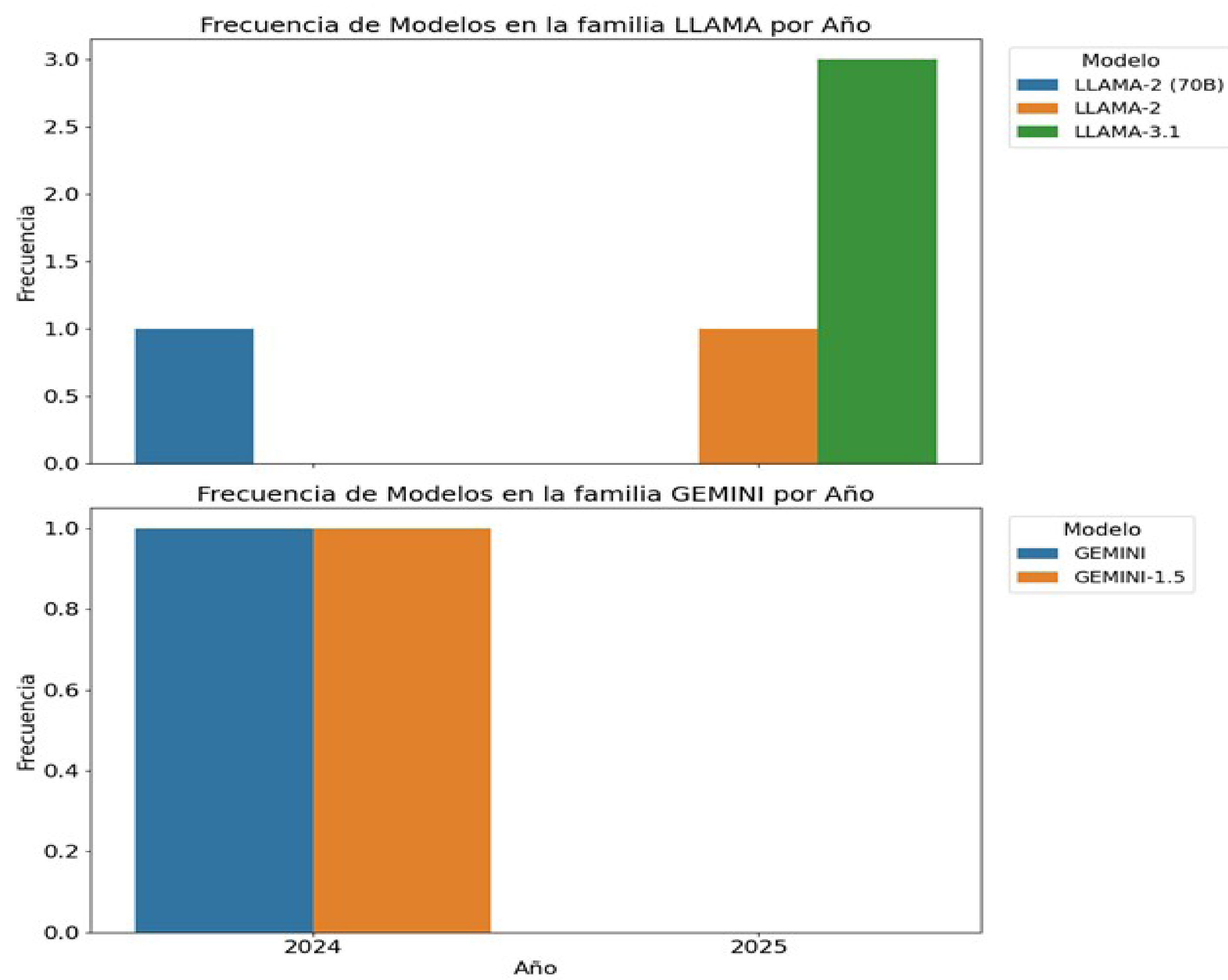

Fig 5. Frequency of use of LLM models between 2023 and 2025. (a) LLAMA family models and (b) family GEMINI

SQ1. Which LLM models have been applied in project formulation?

Table 4 shows the tasks that, in each selected study, were assigned to the LLM for project formulation. The table is ordered according to the number of references.

TABLE 4. TASKS SUPPORTED BY LLMS.

Task	Description	Ref
Effort and time estimation of tasks	Estimate effort, story points, or task duration, enabling more accurate time planning.	[27] [23] [28] [44] [33]
Generation of schedules and project plans	Generate initial schedules and plans with tasks, sequence, and estimated duration, streamlining planning.	[20] [26] [24] [39] [25]
Generation of ideas and design alternatives	Provide innovative and structured ideas for design, supporting brainstorming and option evaluation.	[51] [40] [49] [52] [34]
Early risk identification and management	Identify risks from the initial planning stage and propose mitigation or contingency measures.	[40] [21] [24] [39] [25]
Support in technical design and simulation	Optimize designs, simulate processes, detect errors, and suggest technical and sustainable improvements.	[29] [24] [39] [25]
Resource allocation and planning	Propose allocation of resources (personnel, tools) to optimize schedules and avoid overloads.	[20] [33] [24] [39]
Task decomposition and plan structure	Support project breakdown into hierarchical tasks (WBS), structuring work logically.	[51] [26] [22]
Generation of initial project requirements	LLMs assist in quickly drafting requirements from basic ideas, facilitating the initial project formulation.	[27] [35] [37]
Analysis and refinement of requirements and user stories	Help detect flaws in requirements and user stories, improving clarity and alignment with project goals.	[43] [46]
Cost estimation and budget analysis	Support cost estimation and cost-benefit analysis, facilitating early financial decisions.	[20] [24] [25]

Task	Description	Ref
Preparation of the project charter (objectives, scope, stakeholders)	Assist in drafting the project charter, defining objectives, scope, and stakeholders from an initial description.	[20]
Support in decision-making and prioritization	Support strategic decisions by analyzing data and suggesting alternatives and objective priorities.	[30] [21]

LLMs have broadly supported project formulation: from the generation and refinement of requirements and the drafting of the project charter, to work breakdown, effort and cost estimation, schedule development, resource allocation, early risk identification and management, support in technical design and simulation, the generation of ideas and design alternatives, and assistance in decision-making and prioritization. It is worth noting that the tasks with the strongest evidence of support are effort estimation, schedule generation, design idea generation, and risk identification. This suggests that LLMs are particularly valuable in the early phases of planning, estimation, and creativity, as well as in facilitating documentation and analysis for decision-making.

SQ2. Which LLM models have been applied in project formulation?

Table 5 presents the answer to this research question, with the results ordered by year according to the references that support the findings.

TABLE 5. ADVANTAGES, DISADVANTAGES, CHALLENGES, AND TRENDS.

Year	Advantages	Disadvantages	Challenges	Trends	Ref
2023	• Fast generation of initial plans • Deeper risk analysis • Improvement in technical communication and clarity • Support for creativity in solutions • Conversational interface for access to specialized knowledge	• Lack of understanding of organizational context • Dependence on human refinement (prompts) • Risks of bias and privacy issues • Generic responses without contextual adjustment	• Requires human intervention to include tacit knowledge • Training users in effective use • Management of sensitive data • Continuous model updating • Integration with existing tools	• Focus on prompt engineering • Increasing use of LLMs as copilots in project definition • Integration with Scrum, including educational environments • First multimodal applications and agents	[20] [23] [50] [24] [25] [22]

Year	Advantages	Disadvantages	Challenges	Trends	Ref
2024	• Reduction of time and costs (~50%) • Accuracy and quality in requirement and design definition • Automation of repetitive tasks • Enhanced creativity • Improvement in collaboration and adaptability of proposals	• High dependence on well-formulated prompts • Risk of incorrect or biased responses • Privacy issues with sensitive data • Constant need for validation • Costly models in limited contexts	• Difficulty understanding poorly defined requirements • Lack of clear explainability • Scalability to specialized domains • Need to balance creativity vs. realism • Technical integration with agile platforms and frameworks	• Hybrid human-AI approaches • Integration with techniques such as Retrieval-Augmented Generation (RAG), multitask agents • Prompt repositories as a new practice • Advances toward multimodal tools and specialized assistants for planning	[27] [35] [28] [29] [40] [44] [45] [32] [38] [30] [31] [36] [43] [33] [26] [41] [42] [34] [37] [39] [46]
2025	• Greater efficiency in technical definition • More understandable AI explanations • More creative and tailored proposals • Reduction of effort in repetitive tasks • Flexible application to multiple domains	• Requires more precise prompt engineering • Persistence of errors in novel cases • Biases inherited from training • High deployment and computational costs	• Difficulty incorporating specialized domain knowledge • Lack of context in advanced technical tasks • Ethical definition of human responsibility • Resource control when implementing scalable agents	• Fusion of GenAI with symbolic rules • Intelligent agents with traceability and explicit reasoning • Qualitative evaluation of AI creativity in definition • Transparency as a key axis for reliable adoption	[51] [47] [49] [52] [48]

The use of LLM assistants in project formulation highlights multiple advantages. Among them, the speed and personalization in generating initial plans and proposals stand out, as well as improved team communication by reducing human errors. LLMs can predict risks and suggest optimizations, automating tasks that save time and improve the accuracy of project formulation. Additionally, they contribute greater creative fluency and adaptability when addressing complex problems, offering detailed explanations and decision-making support. However, disadvantages are also documented: the models heavily depend on carefully crafted prompts and sometimes lack the necessary organizational context, leading to inconsistent results. There are also technical constraints (such as token limits) and data privacy concerns. In highly innovative tasks, their originality is often lower than that of humans. For this reason, human oversight is emphasized as necessary to validate their outputs and avoid the omission of key criteria.

The challenges identified include the difficulty of finely adapting the models to specific domains and ensuring the explainability of their responses. Integrating LLM assistants with existing project planning systems without generating incompatibilities is also complex. Moreover, the importance of incorporating specialized technical knowledge into the models and maintaining human responsibility over critical decisions is highlighted.

Regarding future trends, studies point toward hybrid environments: combining the speed of LLMs with human judgment and complementary methods. For example, the integration of techniques such as RAG, the use of multimodal or symbolic reasoning-based models, as well as the application of these assistants within agile frameworks such as Scrum, is discussed. In summary, the progress is moving toward mixed solutions where LLMs serve as a starting point, supported by control mechanisms and explicit qualitative evaluation.

SQ3. What methods have been used to evaluate the effectiveness of LLM assistants in project formulation?

Below, Table 6 summarizes the methods used to evaluate LLM assistants in project formulation. It is ordered from highest to lowest according to the number of references. Each technique is briefly described, ranging from comparisons with humans and expert reviews to automatic evaluations, surveys, interviews, and objective metrics, to facilitate readability and contrast between approaches.

TABLE 6. EVALUATION METHODS FOR LLMS.

Evaluation Method	Specific Techniques	Ref
Comparison with humans or traditional methods (benchmarking)	AI-generated results were directly compared with those made by humans or older methods. Aspects measured included time required, number of errors, compliance with standards, or level of detail.	[20] [40] [44] [30] [26] [42] [48] [37] [22]
Expert evaluation (review of AI-generated results)	Professionals in project management or development reviewed what the LLM generated (e.g., a plan, schedule, or user story) and assessed whether it was correct, useful, and complete. Sometimes, multiple versions were reviewed until they reached good quality.	[51] [45] [32] [49] [43] [52] [33] [39] [25]
Automatic evaluation with other AI (use of evaluator LLMs)	Other AI models were used to review what the LLM assistant produced. For example, similarity to an ideal response was measured using metrics such as BERTScore, or evaluators such as G-Eval were applied to score quality and clarity.	[29] [31] [47] [36]
Surveys/ questionnaires (user evaluation)	Surveys with scales (Likert-type) were applied where users rated how useful, clear, or easy to use the tool was. Open-ended questions were also included so participants could provide feedback in their own words.	[35] [41] [24] [46]
Qualitative interviews (evaluation with users or experts)	In-depth interviews were conducted with individuals who used or analyzed the LLM assistants, asking about their experience, observed benefits, encountered difficulties, and comparison with traditional methods.	[21] [34]
Objective metrics (performance measures)	Concrete data were measured, such as: how accurate the LLM's responses were, how much time it saved, how many errors were avoided, or whether it correctly predicted task effort or duration. Statistical measures such as accuracy and mean error were also used.	[28] [38]

To evaluate the effectiveness of LLMs in project formulation, various methods are employed that combine automatic metrics, statistical analysis, and qualitative evaluation. A common approach is to use automatic metrics to compare generated texts with reference answers: lexical or semantic similarity scores are calculated, and the accuracy of key terms in the assistant's outputs is measured. Complementarily, many studies apply classical statistical analysis (t-tests, ANOVA, correlations, and frequency counts) to compare quantitative results between different models or experimental conditions. Manual qualitative analysis is also carried out: experts review examples of generated responses, identifying patterns, recurring themes, and assessing coherence and relevance of the content.

On the other hand, assistants are assessed through experiments with real users. In controlled tests, specific tasks are assigned to the assistant, and its success rate and response times are measured. User surveys (with multiple-choice questions and satisfaction scales) are used to capture perceptions of answer quality. A/B experiments are also conducted, comparing different model versions to determine which yields better results. To deepen the analysis, semi-structured interviews with participants are carried out, obtaining open feedback on assistant performance. There are also observational studies, where user interaction with the system in real situations is analyzed, and occasionally systematic content analysis of generated outputs (extracting keywords and predominant themes) is performed to validate relevance. Taken together, these methodologies ensure a comprehensive evaluation that combines technical rigor with user experience insights.

SQ4. In which disciplinary field has the use of LLMs been applied for project formulation?

A brief summary of Table 7 is presented, which organizes the disciplinary fields and their application of LLMs according to the number of supporting articles. It includes Project Management (with emphasis on task coordination and orchestration, planning and estimation, and advanced support), Engineering and Design, Artificial Intelligence, Software Engineering, and Business and Economics, along with the associated references for each entry.

TABLE 7. DISCIPLINARY FIELDS OF APPLICATION.

Disciplinary Field	Application	Ref
Project Development	Coordination and orchestration of tasks	[27] [20] [28] [44] [30] [31] [36] [52] [33] [26] [50] [21] [24] [37] [39] [25]
	Planning and estimation	
	Advanced project support	
Engineering and Design	Support for conceptual and technical design, new product development process	[51] [29] [40] [52] [42] [24] [34] [39] [25]
Artificial Intelligence	Information analysis and synthesis, Data science projects	[29] [32] [31] [47] [26]
Software Engineering	Requirements analysis and management	[27] [35] [43] [46]
Business and Economics	Market studies and feasibility analysis	[38] [41]

The use of LLMs in project formulation has been concentrated mainly in the field of Project Development, where the largest number of references are recorded (16 articles) focused on coordination, task orchestration, planning, and advanced project support. In second place, the field of Engineering and Design stands out (9 references), applied to conceptual and technical design and new product development. Applications are also evident in Artificial Intelligence (5 references), especially in information analysis and synthesis for data science projects, and in Software Engineering (4 references) for requirements analysis and management. Finally, in Business and Economics (2 references), LLMs have been explored for supporting market studies and feasibility analysis.

This reflects that, although adoption is cross-disciplinary, project management concentrates most of the documented experiences.

LLMs have been applied in multiple disciplinary areas, in software engineering, their use focuses on requirements analysis and management: they assist in the collaborative creation and refinement of user stories and in the decomposition of functionalities aligned with project objectives. In engineering and design, they contribute to conceptual and technical project design, for example, evaluating safety, reliability, and regulatory compliance criteria for proposed solutions. Finally, in business and economics, they are used in market studies and project feasibility analysis, identifying demand trends and recommending strategies for launching or adapting initiatives.

SQ5. What tools based on LLM or GenAI models have been developed or used to support the MGA in Colombia?

From the search process carried out, no studies were identified that report the use or development of tools based on LLM or GenAI models specifically aimed at supporting project formulation under the MGA. This absence highlights an existing gap, suggesting an emerging field with high potential for future research and technological applications in the context of public project formulation and evaluation in the country.

CONCLUSIONS

The analysis carried out shows that the use of LLM in project formulation has experienced significant growth in recent years. Models such as GPT-3.5, GPT-4, and their variants are the clear leaders, while other models like LLaMA, GEMINI, and alternatives have also begun to be explored. This diversity reflects a technological consolidation that favors the integration of GenAI into multiple stages of the project life cycle.

The tasks in which LLMs have shown the greatest impact include requirement generation and validation, market analysis, resource estimation, collaborative planning, and the creation of simulated environments for pre-implementation testing. These functions have not only optimized time and resources but also improved accuracy and consistency in both technical and strategic decision-making. However, these advantages are accompanied by challenges such as reliance on precise prompting, lack of explainability, and the need to integrate these models into complex organizational environments that require constant human validation.

The evaluation methodologies identified combine quantitative and qualitative approaches, allowing for a comprehensive view of LLM assistant performance. Automatic metrics, controlled experiments, surveys, user studies, and interviews are used, demonstrating a growing interest in understanding not only the technical effectiveness of these models but also their acceptability and usability in real contexts.

One of the most relevant conclusions is the wide range of domains in which these technologies are applied, spanning from software engineering to information analysis and economic feasibility studies. However, when specifically evaluating the Colombian context, an important gap was identified: no studies were found reporting the development or use of tools based on LLM or GenAI to support project formulation under the MGA. This absence represents a strategic opportunity for innovation in the public sector, especially in critical areas such as investment project formulation, but also in the evaluation and monitoring of such projects.

In summary, the implementation of LLM in project formulation is at an advanced stage internationally, but still has room for improvement in contextual adaptation, explainability, and accountability. In the Colombian case, the limited adoption of these tools in MGA-based project formulation and their potential use in management and monitoring reveals an emerging field with high potential for impact. It is suggested that future research and development focus not only on evaluating the technical effectiveness of these models but also on designing solutions aligned with public policy needs, national methodological standards, and ethical governance criteria.

CRediT AUTHORSHIP CONTRIBUTION STATEMENT

N. Fernández Majé: Research, Writing – Original draft, Writing – Revision and editing. C. Cobos-Lozada: Formal analysis, Writing – Revision and editing. H. Ordoñez-Erazo: Formal analysis, Writing – Revision and editing.

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