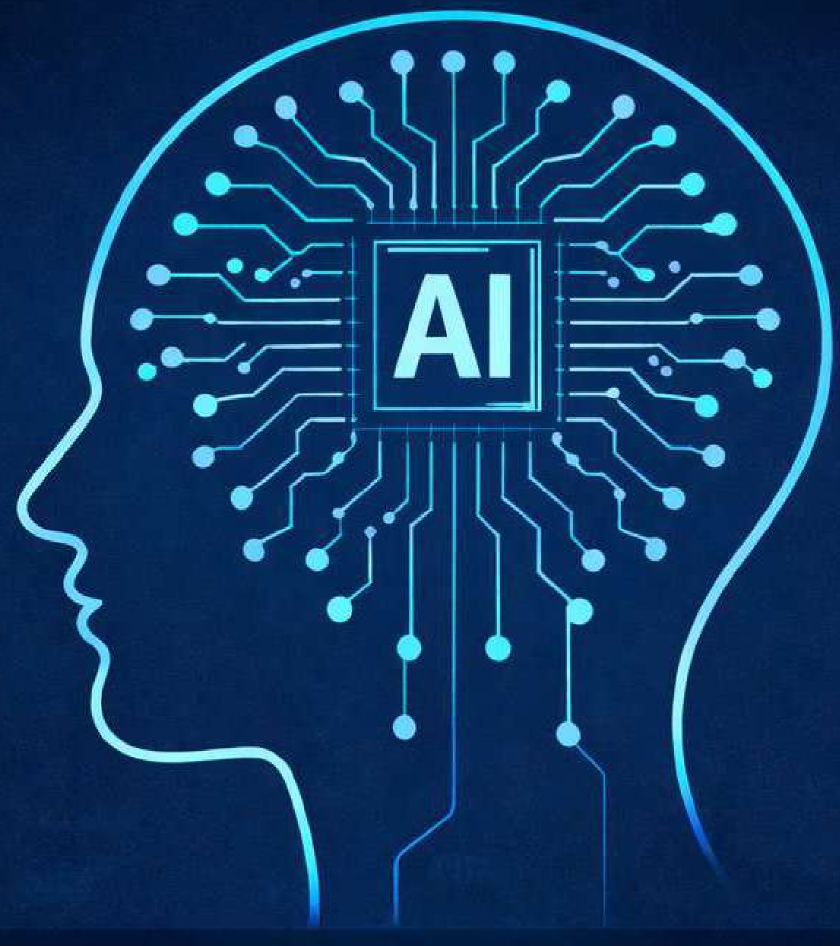
Sebastian Matysik Krzysztof Jaworski

THE USE OF AI IN ACADEMIC WORK



An Interdisciplinary Guide for PhD Students and Young Researchers

Sebastian Matysik

Krzysztof Jaworski

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Introduction

Purpose and Motivation

The dynamic adoption of generative tools, particularly large language models (LLMs), is significantly transforming the practice of academic work. This phenomenon brings both new opportunities such as accelerating literature searches, automating editing, and supporting data analysis and risks, including hallucinations, bias, breaches of confidentiality, and inconsistent publishing requirements for disclosing the use of artificial intelligence.

The scientific monograph “The Use of AI in Academic Work. An Interdisciplinary Guide for PhD Students and Young Researchers” represents an attempt to organize these changes and present coherent methodological and ethical frameworks for young researchers. It was created as a result of the authors’ collaboration during workshops organized by the Doctoral School of the University of Szczecin and is based on teaching experience, consultations with participants, and an analysis of practices related to AI use in scientific research and publications.

The monograph therefore combines conceptual explanations and trends with procedures, checklists, and mini-tasks to facilitate the rapid and responsible implementation of AI in practice.

A key motivation behind this monograph was to equalize access to practical knowledge. Many existing studies focus on technologies, while fewer show how to safely integrate them into a researcher’s workflow and how to report their use in accordance with the policies of leading publishers. The monograph addresses both needs: it synthesizes theoretical foundations and organizes the most important methodological and organizational decisions that young researchers face today when working with AI.

The authors themselves are doctoral students, so in a sense, the book was written also from the perspective of their own needs and the immediate environment of the doctoral school, in a way that best responds to ongoing changes and emerging challenges.

Scientific Objectives

The main objective of the monograph was to identify and assess the impact of artificial intelligence on the research process in academic science, with particular attention to standards of integrity, transparency, and the evolution of publication practices between 2019 and 2025.

Specific objectives:

1. To identify and systematize key forms of AI application throughout the research cycle from literature review to publication of results and to determine their impact on research structure and methodology.
2. To conduct a comparative analysis of policies and standards of leading scientific publishers regarding AI use, identifying common elements and differences in approaches to authorship, disclosure, and accountability.
3. To identify and assess the dynamics of explicit declarations of AI use in scientific publications from 2019-2025 based on data from Google Scholar, Web of Science, and Scopus.

Research Questions

1. What forms and areas of AI application in the research cycle are currently most common, and what risks accompany their use?
2. What elements constitute the shared minimum across publishing policies regarding AI disclosure and author responsibility, and where do significant differences occur?
3. How did the scale of explicit declarations of AI use in scientific publications change between 2019 and 2025 in the three main databases: Google Scholar, Web of Science, and Scopus?

Methodology

A combination of scoping review and narrative review methods was used to analyze articles and monographs published mostly between 2019 and 2025 (as of August 15, 2025) covering studies on AI/LLMs, human–AI interaction, review methodologies, and publishing policies.

Some quantitative data concern explicitly declared use of AI tools in publications, where three sources (Google Scholar, Web of Science, Scopus) were analyzed using a consistent query including tool names (OR operator). Limitations of these databases were considered (a broader spectrum of document types in Google Scholar and stricter criteria in WoS and Scopus).

A review was conducted of the positions of leading scientific publishers (Elsevier, Springer Nature, Taylor & Francis, Wiley, SAGE, IEEE, Emerald) as well as selected examples from Poland. The review identified a shared minimum (no AI authorship, mandatory disclosure of significant use, caution with images and data, confidentiality requirements in peer review) and detailed differences, for example, in the scope of disclosures.

Generative tools were used in the preparation process as editorial, linguistic, and organizational support, as well as for literature search and synthesis. However, all substantive aspects, numerical data, and citations were verified in primary sources, and the bibliography and references were manually checked (DOI, title, year). The use of AI is transparent and consistent with practices recommended by publishers and guidelines for responsible AI use in research.

Publishing policies and model parameters are evolving dynamically; the presented comparisons and recommendations reflect the state of affairs as of April–August 2025. We recommend verifying the current policies of specific journals and institutions and adapting procedures to the characteristics of the discipline and data.

Significance and Usefulness of the Monograph

The study contributes to the scientific literature by providing:

1. A systematization of conceptual foundations and trends related to AI use in science.
2. An empirical quantitative analysis of the growth in explicit AI use declarations (2019–2025).
3. A comparison of publishing policies and identification of a shared canon of responsible AI use principles.
4. A set of tools and checklists facilitating the practical, ethical, and standards-compliant implementation of AI in research and education.

Part I Theoretical Introduction

The first part of the monograph focuses on the theoretical foundations of using artificial intelligence in science. Its aim is to organize key concepts, present the main currents in AI development, and show the dynamics of their integration into academic practice. The knowledge gathered here allows for a better understanding of both the potential and the limitations of new technologies, forming a foundation for further practical considerations. In this way, a young researcher can consciously situate their own experiences within a broader methodological and ethical context.

1. Introduction to AI in Science

The development of artificial intelligence in recent years has transformed the way scientific research is conducted, opening new possibilities in data analysis, literature review, and writing and editing texts. In particular, generative AI and large language models have become tools that increasingly support the work of researchers and doctoral students, both in conceptual tasks and in the practical aspects of preparing publications. This chapter presents definitions of basic concepts related to AI, its main areas of application, and the dynamics of the growing presence of these technologies in science.

1.1 Definitions: AI, ML, LLM, generative AI

Artificial Intelligence (AI)

Artificial intelligence is a field of research and engineering practice focused on designing systems capable of performing tasks that typically require human intelligence and skills such as perception, reasoning, learning, planning, or understanding language. In recent literature, AI is understood as a set of methods including machine learning and deep learning that enable machines to simulate cognitive functions and adapt to data and context (Bajwa, Munir, Nori, Williams, 2021; Xu et al., 2021). Thus, AI can be said to "simulate human thinking and behavior," and in practice, it performs tasks requiring intelligence, from pattern recognition to natural language understanding (Bajwa et al., 2021; Xu et al., 2021).

A distinction is made between narrow AI (systems specialized in single tasks) and the concept of artificial general intelligence (AGI) a system capable of learning broadly and adapting to new situations across multiple domains. Contemporary definitions of AGI emphasize formal, computable models of learning and reasoning, as well as the close connection between intelligence and interaction with the environment (Bennett, 2022).

Importantly, research on AI increasingly highlights its socio-technical nature: AI functions in conjunction with social and institutional practices, which influences both how machine intelligence is defined and the ethical and regulatory requirements it entails (Rezaev, 2021; Owczarczuk, 2023; Bennett, 2022).

Machine Learning (ML)

Machine learning is a subset of AI that involves building models that learn from data rather than being explicitly programmed with rules. In the modern view, ML includes supervised learning (with labeled data), unsupervised learning (discovering structures), reinforcement learning (learning action policies based on rewards), and increasingly common self-supervised learning, where the supervisory signal is generated from the data itself. A key feature is the ability to generalize models improve their performance as more data and feedback become available (Barbierato, Gatti, 2024; Brnabic, Hess, 2021).

Recent reviews describe machine learning as the design of systems in which humans actively correct and supervise both data and model behavior from the annotation stage to interventions during training. This approach increases the quality and reliability of models, especially in tasks that are difficult to fully automate. Current syntheses organize terminology, present taxonomies of techniques, and emphasize that in many scientific applications, effectiveness increases precisely through human–model iteration (Mosqueira-Rey, Hernández-Pereira, Alonso-Ríos, Bobes-Bascarán, Fernández-Leal, 2023; Wu, Xiao, Sun, Zhang, Ma, He, 2022).

Large Language Models (LLM)

LLMs (Large Language Models) are large, pre-trained generative models, usually based on the transformer architecture, that learn to predict subsequent tokens in a text based on very large datasets. A token is the basic unit of text on which large language models operate it can correspond to an entire word, a part of a word, or even a single character. The models learn to predict the next token in a sequence; therefore, the number of tokens determines the maximum span of text they can process at once. Contemporary reviews define LLMs as a class of models typically counted in tens of billions of parameters, which, through data and computation scaling, reveal generalized abilities from summarization and question answering to translation and programming (Zhao et al., 2023; Minaee, Mikolov, Nikzad, Chenaghlu, Socher, Amatriain, Gao, 2024). In scientific applications, LLMs are viewed as a specific case of generative AI focused on natural language (Lu, Peng, Cohen, Ghassemi, Weng, Tian, 2024).

Scaling plays a crucial role, as studies such as those on GPT-3 have shown that increasing model and data size improves performance in the "few-shot" mode without additional fine-tuning (Brown et al., 2020). More recent analyses of scaling laws specify that for a given computational budget, there is a relationship between model size and the number of tokens required for optimal training, known as the "Chinchilla scaling law" (Hoffmann et al., 2022). At the same time, the Foundation Models report describes LLMs as base models trained on broad datasets, easily adaptable to multiple tasks, but also carrying the risk of homogenizing errors in practical applications (Bommasani et al., 2021).

Generative AI

Generative AI encompasses computational techniques capable of creating new content (text, images, sound, video, or molecular structures) based on distributions learned from data. The latest studies conceptualize GenAI as a component of socio-technical systems and highlight its rapid diffusion from DALL·E 2 through GPT-4 to coding assistants, transforming work and communication practices (Feuerriegel, Hartmann, Janiesch, Zschech, 2024). Simultaneously, historical reviews trace the stages of GenAI's development over seven decades and its links with foundation models (He, Cao, Tan, 2025).

The most important generative paradigms today include diffusion models, which have achieved breakthrough synthesis quality (Ho, Jain, Abbeel, 2020), as well as a wide range of methods described in current reviews for example, mechanisms for accelerating sampling or combining with other model classes (Yang et al., 2022). In practice, it is precisely diffusion models and large-scale LLMs, often multimodal, that power the contemporary GenAI landscape (Ho, Jain, Abbeel, 2020; Yang et al., 2022).

The rapid adoption of GenAI raises questions about reliability, bias, transparency, and regulatory frameworks in science and beyond. Recent review studies recommend establishing stable regulatory frameworks and responsible implementation practices for example, in medicine, administration, and education to maximize benefits while minimizing social risks (Owczarczuk, 2023).

1.2 Language Models and Training Methods

Large language models (LLMs) based on transformer architecture have become universal research tools because they can, in a sense, understand and generate text and, with minor adaptation, support tasks from literature summarization to prototype analysis generation (Minaee et al., 2024; Zhao et al., 2023).

Transformers use self-attention, which allows the model to analyze any part of a sentence and learn dependencies across long contexts. In practice, this gave them a significant advantage over earlier approaches such as RNNs or statistical models, which scaled poorly for long texts (Minaee et al., 2024; Zhao et al., 2023). Open-source versions such as LLaMA and LLaMA 2 have enabled rapid academic experimentation (Touvron et al., 2023a, 2023b). Large-scale models such as PaLM have demonstrated that increases in data and computational power result in clear quality improvements (Chowdhery et al., 2022).

Model Families:

• Encoder-only (e.g., BERT, DeBERTa) – best suited for understanding, classification, and information extraction tasks. Typically trained through token masking (He et al., 2021).

• Decoder-only (e.g., GPT-3/4) – designed for generation, trained by predicting the next token, and perform well in zero/few-shot settings (Brown et al., 2020; Minaee et al., 2024).

• Encoder–decoder (e.g., T5/BART) – convenient for text-to-text transduction tasks such as translation and summarization, often chosen for tasks requiring both understanding and generation (Zhao et al., 2023).

Model Training Methods:

1. Self-supervised pretraining - the model learns on unlabeled data, either by masking parts of words (BERT-, DeBERTa-type variants) or predicting the next token (GPT-type variants). Large-scale data and computation are key to quality (He et al., 2021; Chowdhery et al., 2022; Minaee et al., 2024).
2. Task adaptation - without full retraining:
   • Prompting and in-context learning**:** a well-designed instruction and examples in the input are sufficient (Brown et al., 2020).

   • Instruction tuning**:** fine-tuning on instruction–response datasets increases the model's adherence to commands (Wei et al., 2022; Chung et al., 2024).

   • RLHF / DPO**:** aligning model behavior with human preferences, either via a reward model (RLHF) or directly from preference pairs (DPO) (Ouyang et al., 2022; Rafailov, Sharma, Mitchell, Ermon, Manning, Finn, 2023).

   • PEFT – parameter-efficient fine-tuning**:** instead of updating all weights, small matrices are modified (LoRA) or fine-tuning is performed in low precision (QLoRA), significantly reducing hardware costs (Hu et al., 2022; Dettmers et al., 2023).

   • Retrieval-augmented generation (RAG, RETRO): the model retrieves text fragments from an external database during operation, improving factual accuracy and currency without embedding all knowledge into parameters (Borgeaud et al., 2022).

Main Challenges in Model Training:

- Data and computation cost – performance improves with scale, but budgets are limited. The "Chinchilla" principle suggests increasing the number of tokens rather than model size for a given budget (Hoffmann et al., 2022). PEFT (LoRA/QLoRA) helps in practice (Hu et al., 2022; Dettmers et al., 2023).
- Long context - classical attention has quadratic cost with respect to sequence length. Improvements such as *FlashAttention* (faster, more efficient attention), *ALiBi* (extrapolation to longer sequences), and *long-context architectures* (LongNet) extend usable context and efficiency (Dao et al., 2022; Press, Smith, Lewis, 2022; Ding et al., 2023).
- Domain adaptation – in specialized domains such as medicine or law, it is best to combine small-scale parameter fine-tuning (PEFT) with external retrieval (RETRO, RAG), which improves relevance and reduces hallucinations (Borgeaud et al., 2022; Minaee et al., 2024).

1.3 AI Tool Interfaces: Chat, API, Plugins, Extensions

In recent years, large language models (LLMs) made available via APIs have gained enormous popularity in science and technology, finding wide applications across disciplines (Zhang et al., 2025). An increasing number of studies describe the integration of LLMs such as GPT-3 and GPT-4 with research tools and academic workflows (Wang, Hu, Huang, Li, Zhang, Ning, Zhu, Li, Ye, 2024).

Systematic literature reviews indicate that these models are used in various fields for example, geoinformatics, chemistry, and biological sciences for automating analyses, generating scientific text, or supporting experiments. These models are becoming part of scientific infrastructure, supporting researchers at multiple stages of the research process (Wang et al., 2024; Zhang et al., 2025).

LLMs are becoming an element of research infrastructure: they automate analyses, support scientific text generation and editing, and assist in conducting experiments (Wang et al., 2024; Zhang et al., 2025). The chat interface enables iterative work in natural language consultations, clarifications, summaries. The API, an interface allowing programs to exchange data and cooperate, enables programmatic integration and large-scale automation of processing. Plugins provide access to external tools and up-to-date data during interaction, while extensions embed models directly into applications such as editors, IDEs, and browsers without changing the working environment (Wang et al., 2024).

Numerous empirical studies indicate that LLMs can act as scientific copilots: they summarize publication content, extract information, generate and translate text fragments, assist in programming (e.g., analysis frameworks), and even plan research steps (Zhang et al., 2025). Integration with data management systems and statistical software streamlines workflow and allows researchers to focus on interpreting results while maintaining critical verification of model-generated content (Wang et al., 2024; Zhang et al., 2025).

The chat interface supports iterative work in natural language refinement, prompt chaining, multi-step explanations and, as confirmed by Jakesch et al. (2023), can enhance writers' productivity and confidence, while also changing the dynamics of the writing process and the need to design AI support that strengthens user agency. Studies by Li, Liang, Peng, and Yin (2024) show that generative AI assistance improves writers' performance and self-evaluation, and that the tool's design affects output quality. At the same time, empirical work reveals that co-writing with a model can influence authors' content and opinions, for example through the risk of assistant bias in dialogue, reinforcing the need for transparent interfaces and verification practices (Jakesch et al., 2023; Jiang et al., 2024).

From a technical perspective, APIs enable three main patterns:
(1) RAG (Retrieval-Augmented Generation) – attaching external knowledge through search or indexing (reduces hallucinations, enables model updates with domain data);
(2) Tool-use / function calls – allowing the model to use tools and services (calculators, search engines, databases) during generation;
(3) Agent architectures – combining reasoning and action in decision loops.

Recent reviews confirm that RAG has become an engineering standard for scientific applications, as it systematically improves accuracy and credibility (Gao et al., 2023; Fan et al., 2024). Meanwhile, tool-use and action planning are described by works such as Toolformer self-learning of API calls by LLMs and ReAct interleaving reasoning and action traces, forming a foundation for LLM autonomy in science (Schick et al., 2023; Yao et al., 2023).

A concrete laboratory example: the Coscientist system (Nature) integrates GPT-4 with search, code execution, and APIs controlling laboratory equipment to autonomously plan and conduct chemical reactions; similarly, LLMs can generate robot scripts from natural-language instructions (Boiko et al., 2023; Inagaki et al., 2023).

Plugins extend model capabilities by invoking third-party services during dialogue such as publication databases, computations, or web browsing and integrating the results into responses. The first comprehensive security study of the ChatGPT plugin ecosystem (ASE 2024) revealed vulnerabilities in authentication and data protection, as well as unequal distribution of plugin functionalities; the authors proposed a three-layer security assessment model (user–developer–store operator) and recommendations on "least privilege" principles and security reviews (Yan et al., 2024). In scientific practice, this means that when using plugins for example, for literature searches or downloading full texts institutions should enforce permission control and audit call logs for compliance with data policies.

Extensions embed LLMs directly into work tools such as editors, IDEs, and browsers, reducing cognitive friction and accelerating workflow. In IDEs, the strongest empirical evidence comes from controlled GitHub Copilot studies: programmers with access to the assistant completed tasks faster by an average of ~56% in one RCT and further field and RCT workplace studies confirm increases in productivity and subjective satisfaction (Peng et al., 2023; RCT 2024).

In office suites such as Microsoft 365 Copilot, the architecture links the user's context with the model within M365 service boundaries, with access control at the identity and permission level, which is crucial when working with documents and research data (Microsoft, 2025).

1.4. History of Writing Support Tools – From Translators and Grammarly to Artificial Intelligence

The contemporary ecosystem of tools can be divided into four categories:

- Machine translators
- Grammar and style checkers (e.g., Grammarly)
- Paraphrasers and intelligent suggestions
- Generative language models (LLMs)

Research in language pedagogy and academic writing shows a shift from correcting existing text to proactively co-creating content and style (Godwin-Jones, 2022; Gustilo, Ong, Lapinid, 2024).

The popularization of neural machine translation around 2016 improved fluency and adequacy, effectively enabling writing in one's native language followed by post-editing in English. Empirical studies in secondary schools showed that using Google Translate with post-editing significantly improved writing quality measures in L2 (Cancino, Panes, 2021). For non-native English authors, this tool has become routine support for preparing drafts and understanding literature (Cancino, Panes, 2021).

Compared to traditional spell-checking, the new generation of tools provides real-time, contextual suggestions from subject-verb agreement to sentence shortening and tone adjustment. Fitria (2021) found a significant improvement in students' writing quality after applying Grammarly's suggestions, illustrating the potential of such tools to eliminate surface errors and improve stylistic coherence. At the same time, literature describes the integration of suggestion and auto-completion features in broader writing instruction scenarios (Godwin-Jones, 2022).

Paraphrasing tools and auto-complete features shift the focus from correction to active editing on one hand promoting clarity, but on the other raising questions about the integrity of authorial contribution. Reviews of university policies and practices indicate that academia views these tools as useful but requiring transparency and usage guidelines (Gustilo et al., 2024).

LLMs such as GPT-4 and GPT-5 enable the creation of summaries, literature reviews, and preliminary drafts of method or discussion sections, significantly shortening the initial editing process. At the same time, the literature highlights risks hallucinations, unintentional self-plagiarism, and stylistic homogenization hence the need for fact verification and clear disclosure of tool use (Dehouche, 2021; Gustilo et al., 2024).

Systematic reviews document the rapid incorporation of LLMs into research practices across many areas, including analysis automation, writing support, and result synthesis (Wang, Hu, Huang, Li, Zhang, Ning, Zhu, Li, & Ye, 2024). For doctoral students, this also means a transition from correction tools to writing-process assistants under the condition of maintaining human subject-matter oversight, post-editing, and transparency (Wang et al., 2024; Gustilo et al., 2024).

When working on a manuscript, it is advisable to:
(a) combine NMT (Neural Machine Translation) with careful post-editing (Cancino & Panes, 2021),
(b) use grammar and style checkers to improve linguistic coherence,
(c) employ LLMs for sketching or reformulating sections but verify all content and disclose tool usage in the methodology or acknowledgments section (Gustilo et al., 2024; Dehouche, 2021).

1.5. The Growth of Scientific Publications Written with the Use of AI

An analysis was conducted to examine how rapidly the number of scientific papers in which authors explicitly declare the use of AI tools in the research or editorial process has been increasing. The analysis covers three sources: Google Scholar, Web of Science, and Scopus, for the years 2019–2025, with 2025 counted up to August 15. The same query with the OR operator was used across all databases, including the exact names of tools: "scite.ai" OR "notebooklm" OR "SciSpace" OR "researchrabbitapp" OR "thesify.ai" OR "paperpal.com" OR "paperguide.ai" OR "elicit.com" OR "chatpdf.com" OR "textero.io" OR "consensus.app" OR "epsilon-ai" OR "jenni.ai" OR "getcoralai.com" OR "scholarai.io" OR "powerdrill.ai"

Thus, the analysis did not measure the number of AI-generated scientific publications but rather papers that explicitly mention specific tools in the methods, acknowledgments, or disclosures.

According to data from Google Scholar presented in Figure 1.1, the following numbers were recorded: 699 publications in 2019, 790 in 2020 (an increase of 13.02 percent year-over-year), 1,050 in 2021 (an increase of 32.91 percent), 1,100 in 2022 (an increase of 4.76 percent), 2,150 in 2023 (an increase of 95.45 percent), 5,300 in 2024 (an increase of 146.51 percent), and 7,160 in 2025 as of August 15 (an increase of 35.09 percent compared to 2024). The ratio of the 2024 value to that of 2019 is 7.582, and the ratio of 2025 to 2019 is 10.243. The average annual growth rate for 2019-2024 was 49.95 percent, confirming the accelerating nature of the phenomenon after 2022.

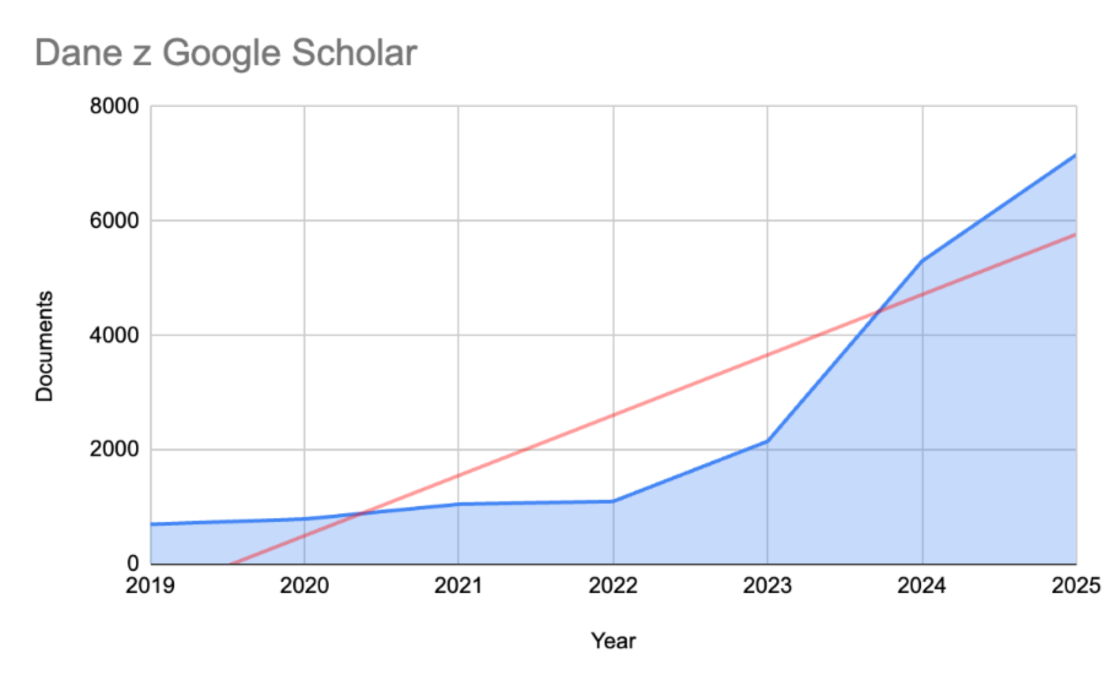

Fig. 1.1. Number of Publications Mentioning AI Tools in Google Scholar (2019–2025)
Source: Author's own elaboration based on data from Google Scholar (access date: 15.08.2025)

Data from Web of Science and Scopus confirm this dynamic, although at a lower absolute level, as shown in Figure 1.2. The following were recorded: 21 publications in 2019, 24 in 2020 (an increase of 14.29 percent), 51 in 2021 (an increase of 112.50 percent), 33 in 2022 (a decrease of 35.29 percent), 64 in 2023 (an increase of 93.94 percent), 164 in 2024 (an increase of 156.25 percent), and 207 in 2025 up to August 15 (an increase of 26.22 percent compared to 2024).

The ratio of the 2024 value to that of 2019 is 7.810, and the ratio of 2025 to 2019 is 9.857. The average annual growth rate for 2019–2024 was 50.84 percent. The only decline in 2022 indicates a temporary slowdown or indexing delay, followed by a sharp increase in subsequent years.

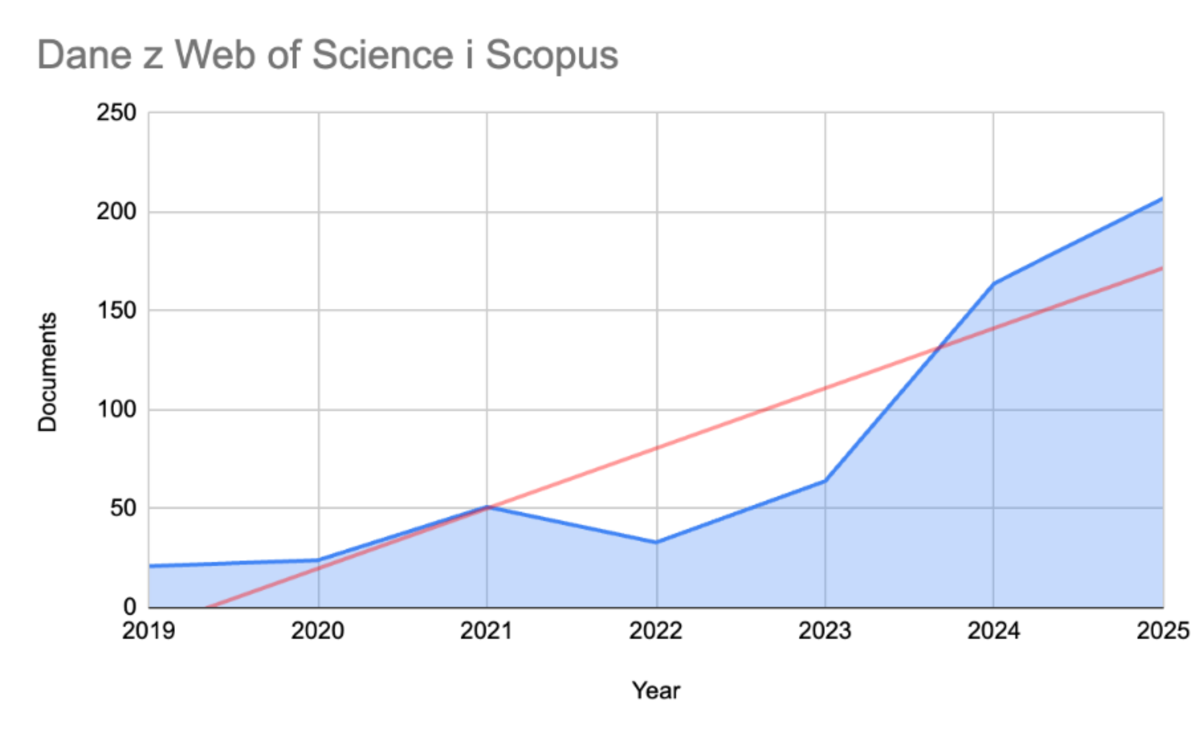

Fig. 1.2. Number of Publications Mentioning AI Tools in Web of Science and Scopus Databases (2019–2025)

Source: Author's own elaboration based on data from Web of Science and Scopus (access date: 15.08.2025)

The convergence of trends across databases suggests that 2023 was a turning point: tools for literature analysis, summarization, and editorial support began to be systematically disclosed in publications. In research practice, it is desirable to consistently indicate the names of the tools used, along with the access date or version, to document queries and parameters, and to verify AI-generated content against primary sources. The choice of tool should correspond to the nature of the task, whether it concerns literature search, text editing, or knowledge organization.

It is important to emphasize the measurement limitations: only publications explicitly mentioning the tool's name are counted (some uses remain invisible or are described differently). Google Scholar covers a broader spectrum of document types, which favors overestimation, while WoS and Scopus apply stricter criteria. Despite these differences, the collected data lead to a clear conclusion: between 2019 and 2025, a dynamic and accelerating growth in declared use of AI tools in the publication process has become established, and the values recorded up to August 15, 2025, exceed the 2024 levels in both data sets.

Summary of Chapter 1

This chapter has shown that artificial intelligence, especially generative models, is becoming an integral part of the modern scientific toolkit. It explained the fundamental concepts and presented examples of their application in research practice, emphasizing both the benefits and limitations associated with these technologies. The collected analyses indicate that the dynamic growth in the number of AI-based publications demonstrates a lasting change in the way knowledge is created one that requires young researchers to cultivate critical evaluation, transparency, and responsibility. AI in science is no longer merely an auxiliary tool but a full-fledged element of the research process, co-shaping its methodology and practice.

2. Synergy of AI and Humans

Technology continues to evolve at an exponential pace. Constant changes in interfaces and the emergence of new functionalities can be overwhelming. In the work of researchers and educators, there is a need for timeless and universal frameworks approaches that strengthen the capacity for conscious engagement with digital tools. Despite the dynamism of these transformations, it is worth grounding the use of generative artificial intelligence on a solid foundation. There is a clear need to establish a perspective that enables decision-making and action regardless of how rapidly or extensively GenAI-based tools continue to develop.

The search for this foundation on which the synergy between human and machine capabilities can be built begins with the assumption that doctoral students and young researchers are immersed in a continuous process of learning. This is the element that allows research projects to achieve their intended goals while their authors develop and expand their competencies. The use of generative artificial intelligence can both enhance and deepen these processes, but it can also adversely affect the didactic and scientific craft if applied unreflectively.

2.1. The Learning Process

The previous chapter provided definitions and explanations of what artificial intelligence is in a technical sense. However, as a technology increasingly intertwined with the conduct of scientific research, it requires a broader perspective.

"AI is not simply an afficiency booster but a force shaping the nature of knowledge production and dissemination. By understanding its mechanics, leveraging its strengths, and mitigating its weaknesses, scholars can harness AI's potential while maintaining the integrity of academic inquiry." (Jemielniak et al., 2025, p. 10)

An essential aspect of using AI technologies lies in recognizing, refreshing, and expanding our human potential. Both elements deepening knowledge about technology and self-knowledge are key to fostering collaboration with AI that is grounded in synergy.

At the same time, it is crucial to acknowledge that as young scientists, researchers, and educators, we participate in a lifelong learning process. This process permeates our conceptual, research, dissemination, and evaluation activities, as well as our interpersonal relationships. For this reason, learning is one of the core areas worth pausing on in this chapter.

It will be interpreted through the lens of constructionism, followed by an analysis of transversal competences to show how different levels of engagement with new technologies activate distinct layers of competence and what conditions must be met for the process of synergy to be based on the conscious use of generative AI and human potential.

The following reflections are accompanied by the words of Seymour Papert: "The proper use of computers is not simply learning how to use computers and computer ideas, it is learning when to use them." (Papert, 1981, p. 176)

2.2. Learning from a constructivist perspective

Learning is an active process through which individuals construct knowledge from their experiences in the world (Bruckman & Resnick, p. 214). This perspective derives from Piagetian constructivism and was further developed by Seymour Papert, who added a crucial dimension: people construct new knowledge most effectively when they engage in building artifacts that have personal meaning to them (Bruckman & Resnick, p. 214).

First, in this view, learning requires an active stance from the learner, who intentionally transforms their own cognitive network. Second, the process is coupled with the creation of external artifacts for instance, essays, analyses and syntheses of research results, computer programs, or other solutions.

Artifacts may also include prompts or other tools and methods developed to support work with generative artificial intelligence.

2.3. The learning cycle

In the adopted perspective, the learning process is often illustrated as a cycle through which its successive stages unfold. Mitchel Resnick proposed the concept of the “creative learning spiral,” as presented in Figure 2.1.

Fig. 2.1. The Creative Learning Spiral

Source: (Resnick, 2017)

It is a process that begins with an idea formed in the mind, which then takes shape through action, play, sharing with others, and reflection only to begin again in a new, deeper cycle. This model, illustrated in Figure 2.2, is conceptually very close to the experiential learning cycle proposed by David Kolb.

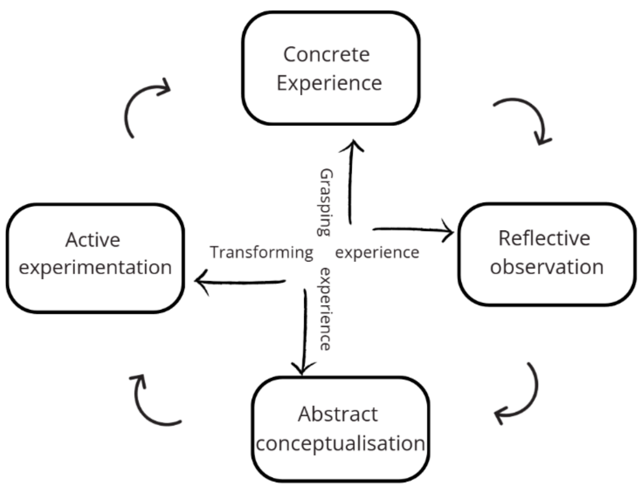

Fig. 2.2. Experiental learning cylce

Source: (Kolb, 2024)

Both of these frameworks emphasize the value of personal experience as well as deep reflection and (re)interpretation. They describe, in a universal way, the continuous nature of learning and the importance of profound engagement in cognitive and exploratory activity.

The sequence of stages in these models indicates that learning is based on repetition, through which we gradually deepen our competences. Taking care of one's own intellectual craft requires effort, engagement in the process of thinking, and as Seymour Papert put it "thinking about thinking" (Papert, p. 39). This enables one to build a cognitive and operational network in a critical and creative way, which we use, among other things, in research work. Therefore, it is essential to consciously cultivate the value of in-depth work, which allows for the development and refinement of the capacity for deep thought, evaluation, and reflection.

"Researchers must maintain rigorous analytical standards, treating AI-generated outputs as preliminary insights requiring thorough examination, validation, and refinement. The objective is to enhance, not outsource, the intellectual process, ensuring that human expertise, domain knowledge, and academic judgment guide research conceptualization." (Jemielniak et al., 2025, p. 30)

At the same time, the use of generative AI entails cognitive and ethical risks. One of them is the phenomenon of cognitive offloading, understood as the use of external means to perform cognitive tasks (Jose, Cherian, Verghis, 2025). This may lead to the simplification of thought processes and excessive dependence on algorithms, which in turn reduces the ability for deep learning and metacognitive reflection. Another risk is the unconscious reproduction of errors and biases embedded in the data on which AI models are trained. Therefore, it is necessary to implement protective strategies that include systematic self-reflection, verification of sources and outputs, critical analysis of content-generation processes, and maintaining a balance between the use of digital tools and traditional forms of intellectual work.

2.4. Deep Learning - Characteristics and Supporting Practices

In the academic literature, deep learning is defined as a process that goes beyond mechanical memorization of content and instead involves a profound understanding, integration with prior knowledge, and deliberate application across diverse contexts (Marton & Säljö, 1976). Its essence lies in the active processing of information and the ability to construct durable and interconnected cognitive structures. In this process, new knowledge does not replace existing mental schemas but rather develops and enriches them, providing greater coherence and usability. It is also a cumulative process, in which each successive layer of understanding builds upon previous experiences, enabling deeper and more critical comprehension of the phenomena under study.

From the perspective of young researchers, maintaining the capacity for deep learning requires a conscious avoidance of superficial strategies that reduce cognitive effort and encourage passivity. Instead, the ability to engage in deep learning can be strengthened by cultivating self-reflection, continuously expanding and connecting existing knowledge, and seeking new contexts for its application.

In this sense, learning becomes not only a process of accumulating information but also a means of shaping the researcher's identity. The researcher becomes a person capable of critical, creative, and responsible knowledge creation in a world where technology including generative artificial intelligence constitutes an integral part of the cognitive environment.

2.5. Iteration that connects

In the constructivist perspective, the learning process is not merely an act of acquiring knowledge but, above all, an active, spiral movement between experience, reflection, creation, and renewed action. Both Mitchel Resnick's creative learning spiral and David Kolb's experiential learning cycle reflect this dynamism. They emphasize the necessity of repeated experience and the gradual deepening of competences. In both Resnick's and Kolb's models, the key lies in the transition from idea to action, from action to reflection, and from reflection to new, refined actions.

In research practice, this rhythm takes the form of a universal cycle: from formulating research questions, through designing methodology, collecting and analyzing data, to verification, validation, and publication of results (Creswell, 2018).

Generative artificial intelligence, when appropriately integrated into this process, can enhance each of its stages. In the conceptualization phase, AI can support idea generation by providing diverse perspectives. During prototyping and experimentation, it can assist in rapid hypothesis testing, tool creation, or framework development. In the stages of analysis and validation, it may act as a reader offering feedback, which the researcher then critically evaluates.

Integrating these three perspectives Resnick's, Kolb's, and the universal research cycle reveals that both the learning process and the research process are inherently spiral and iterative. AI does not replace thinking; rather, it can serve as a catalyst, accelerating transitions between stages and deepening reflection. According to Mitchel Resnick, GenAI does not merely become an assistant in this process but an additional resource available to support research work (Resnick, 2025). This shift in perspective helps to avoid excessive personalization while requiring that AI-generated content be approached in the same way as any other source of information.

Table 2.1. Correspondence Between Resnick's, Kolb's, and Research Cycle Stages, and the Role of Generative

Resnick's Stage	Kolb's Stage	Stage of Scientific Research	Role of Generative AI
Idea	Conceptualization	Formulating research questions	Providing inspiration, analyzing trends, generating questions and hypotheses
Create	Conceptualization / Experience	Designing methodology and research tools	Creating prototypes of tools, scripts, and models; supporting the development of research procedures
Play	Experience / Experimentation	Data collection and analysis	Automating preliminary analysis; generating code; producing initial visualizations
Share	Reflection	Verification and validation of findings	Suggesting interpretations, detecting inconsistencies, providing feedback
Reflection	Reflection	Publication and dissemination of results	Assisting in text editing, language adaptation, and preparing various publication formats
Reconstruction of the idea	Return to conceptualization	Generating new research questions and areas	Identifying research gaps and generating further directions for inquiry

Source: own work.

2.6. Competences in the Field of Generative AI

Competence is defined as a function of knowledge, skills, and attitude (European Parliament and the Council, 2006, p. 3), resulting from the cultivation and development of human cognitive and social abilities. In the context of technological advancement, including generative artificial intelligence, transversal competences are particularly essential and relevant. They represent a crucial domain that determines the scope and level of human potential in working with GenAI. Without them, it is difficult to carry out scientific, research, and didactic tasks at a meaningful level.

To build synergy between humans and technology, it is necessary to identify which human competences require strengthening in order to make such synergy possible. Synergy here is understood as a phenomenon in which the outcome of cooperation exceeds the sum of individual contributions.

The presentation of competences should begin with those that directly concern the use of generative AI. They constitute the equivalent of digital literacy in the field of artificial intelligence. The literature introduces the concept of twelve key competences necessary for the conscious use of GenAI. This is a set of skills, attitudes, and knowledge that a researcher, educator, or any advanced AI user must develop to use these tools effectively and responsibly (Annapureddy et al., 2025).

The model proposed by Annapureddy, Fornaroli, and Gatica-Perez (2025) outlines competences ranging from fundamental orientation in the domain of artificial intelligence, through proficiency in operating generative tools, to conscious ethical reflection on their use. These competences, organized from basic to advanced, form a logical educational sequence resembling a spiral structure: from mastering foundational knowledge, through developing specific skills, to the level of lifelong learning that permeates the entire process.

Such progression demonstrates that effective learning in working with GenAI occurs iteratively, layer by layer, in the spirit of Kolb’s and Resnick’s models, where reflective experience leads to the continuous deepening of competences.

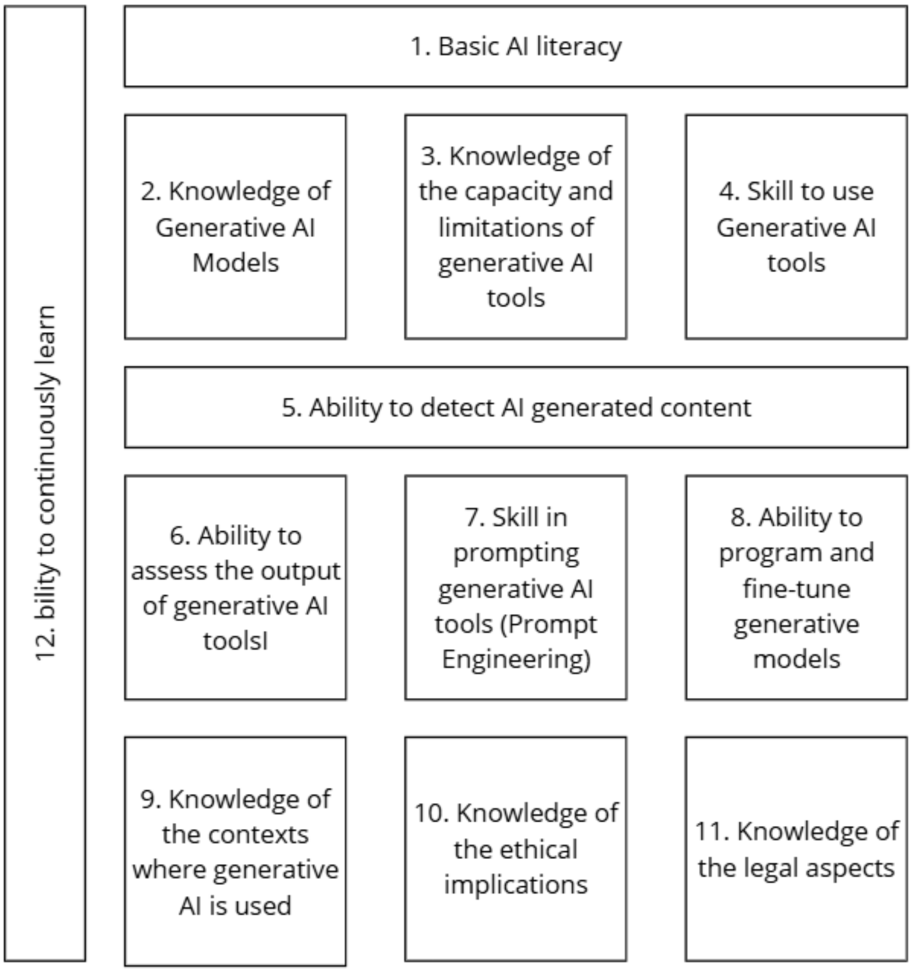

Fig. 2.3. Diagram of the 12 generative AI competencies

Source: (Annapureddy i in., 2025)

The above components constitute the foundation of knowledge, skills, and attitudes that should serve as the basis for continuous development and as a framework for the meaningful use of generative AI. However, to achieve true synergy, we must look deeper toward what, from a human perspective, remains a unique and universal reservoir of competences.

2.7. Transversal Competences

Among many typologies of competences, one of the most recognized is the 4C model, formulated by the Partnership for 21st Century Skills (Washington, D.C., 2003). This model includes four key areas: collaboration, critical thinking, creativity, and communication. The literature also features other classification proposals that complement or modify this set. An example is the "Skills for Learning" model developed by CEDEFOP, which, alongside critical thinking and creativity, also highlights problem-solving, adaptability, digital agility, and a lifelong learning mindset (CEDEFOP, 2024).

Regardless of the adopted typology, these competence models share a broad perspective encompassing cognitive, social, and practical dimensions. They also exhibit common features that can be described in terms of transgressivity (Nowotny, 2000) and transversality (CEDEFOP, 2023). They are characterized by the interpenetration of individual competences, their mutual reinforcement, and the use of shared resources in the course of performing complex activities both individually and collectively. In practice, this means that competences do not function in isolation but form dynamic and interrelated systems in which change in one area affects the scope and possibilities of the others.

The understanding of transversal competences is not limited to the sphere of collaboration and interpersonal relations but also encompasses the ability to work effectively in cooperation with digital technology, including various generative AI solutions. Working with GenAI requires not only communication competences understood as the ability to precisely formulate queries and interpret machine responses but also the skills of cooperation in achieving defined objectives, creative and unconventional project development and implementation, and critical evaluation of the generated results.

Understood in this way, these competences can be expressed through the following dimensions:

- communication as interaction between a human and a language model–based system;
- collaboration as a process of jointly constructing knowledge based on algorithmically generated proposals;
- creativity as the ability to use AI-generated content as material for further work;

• critical thinking as the continuous verification of the accuracy, coherence, and reliability of information provided by technology.

In this context, the transversality of competences involves both transcending disciplinary and cognitive boundaries and expanding the space of action through the synergistic combination of human potential with machine capabilities. Such a perspective implies that, while reducing time and effort in repetitive or tedious tasks, researchers should increase their engagement in activities that elevate their projects to a higher level also through unconventional approaches to GenAI.

Since transversal competences form a dynamic and interdependent system influenced by both our conscious and unconscious experiences, it is important to guide the learning process in ways that allow these competences to be strengthened and expanded. Integrating GenAI into research routines and workflows is interwoven with the knowledge, skills, and attitudes that evolve through ongoing development. Hence, there is a need for reflective monitoring of how the use of these tools affects the professional practice of young educators and researchers.

2.8. SAMR Model

The SAMR model, proposed by Ruben Puentedura (2010), is a four-level framework describing the ways in which technology is used in the educational process: substitution, augmentation, modification, and redefinition. In the context of doctoral students' and young researchers' work with generative artificial intelligence, this model can serve as a tool for reflection and for identifying the level of GenAI integration in research and teaching practice. It allows users to determine their current stage of technological integration and to recognize how the development of their competences is connected to the use of AI tools at higher levels of advancement.

From the perspective of transversal competences, each level of the SAMR model reflects a deeper degree of their application. At the lowest level substitution the role of GenAI is limited to functioning as a digital version of traditional tools, such as automatic note-taking, translating materials, or searching for information. Critical thinking is applied in a narrow sense, confined to basic evaluation of accuracy; creativity remains operational; communication is simple; and collaboration is incidental.

At the augmentation level, the use of technology can support deeper analysis and optimization of research activities. Critical thinking includes comparing and verifying sources; creativity involves generating alternative solutions; communication becomes more intentional; and collaboration turns into a conscious process of exchanging data and interpreting results.

At the modification level, the researcher employs GenAI to integrate it structurally with research and creative processes. Its use supports problem modeling, simulations, and the generation of possible research scenarios. Critical thinking encompasses consequence analysis and the selection of optimal strategies; creativity manifests in the creation of new research concepts; communication acquires an argumentative and questioning character; and collaboration involves task coordination and complex problem-solving.

At the highest level redefinition it becomes possible to design innovative research and teaching activities that expand the scope of inquiry in ways that would be inaccessible or impossible to implement without technological solutions. The 4C competences reach their broadest scope here: critical thinking includes metacognition and the evaluation of impacts, for example on the social environment; creativity assumes a transformational form; communication becomes multichannel and intercultural, encompassing diverse perspectives; and collaboration is based on openness and continuous exchange. A synthesis of this description is presented in Table 2.2.

Table 2.2. Levels of Competence in the SAMR Model

SAMR Level	Critical Thinking	Creativity	Communication	Collaboration
Substitution	Basic evaluation of content accuracy and relevance	Operational adaptation of existing ideas	Simple information exchange	Optional, ad hoc collaboration
Augmentation	Comparing sources, verifying data	Generating alternative solutions, optimizing processes	Conscious exchange of data and opinions	Task sharing and initial coordination
Modification	Analyzing consequences, selecting strategies, problem modeling	Designing new research concepts	Argumentative, multi-stage communication	Coordination and joint problem-solving
Redefinition	Metacognition, ethical and social reflection	Transformational creativity, breakthrough innovations	Multichannel, intercultural communication	Openness and flexible exchange

Source: author's own elaboration

The development of one's own research competences and the accumulation of experience in teamwork with both humans and machines are prerequisites for advancing to higher levels of the SAMR model when working with GenAI. It is precisely the progression within the 4C framework that allows us to move closer to the model of human–machine synergy.

2.9. Ethical Dimension of Synergy

In the context of developing one's research and teaching practice, it is important not to overlook the ethical aspect. This theme will appear in other parts of this publication as well; however, at this point, two general perspectives will be indicated, which may provide a universal and broad foundation for creating the conditions necessary for synergy.

2.10. AI Act

The European Union's Artificial Intelligence Act (AI Act, 2024) is the first comprehensive legal document of its kind globally, regulating the domain of artificial intelligence. Although complex and extensive, several elements from the Act are particularly relevant and universal for our discussion. Its foundation lies in the protection of fundamental values that ensure that the development and implementation of AI technologies do not contradict democratic principles or human rights.

The document refers to the Charter of Fundamental Rights of the European Union, which includes, among others, the right to human dignity, freedom and equality, protection of personal data and privacy, the prohibition of discrimination, the right to a fair trial, freedom of expression, as well as the right to education and participation in social and cultural life. This regulation emphasizes that its purpose is not to inhibit innovation, but to ensure that technological progress strengthens rather than undermines the foundations of social life. In this sense, the AI Act is not only a legal document but also a profoundly axiological one, pointing to the necessity of developing technology in harmony with the values that constitute European identity. This perspective highlights that within synergy although it combines human and technological potential it is the human perspective that must be prioritized, protected, and developed.

2.11. Lines in the Sand

This human-centered viewpoint, along with guidelines for its practical implementation, was articulated in a more accessible form than the AI Act by Mitchel Resnick and his team (Resnick, 2025). These guidelines were developed to support educational ecosystems designed by the Lifelong Kindergarten group and the Scratch Foundation. They outline values and boundaries, poetically referred to as Guiding Stars and Lines in the Sand, and are presented as follows (Resnick, 2025):

Guiding Stars**:**
– Creativity**:** fostering self-expression;
– Agency**:** ensuring that the power to decide and choose remains in human hands;
– Equity**:** providing free, fair, inclusive, and accessible participation;
– Community**:** emphasizing the importance of human connection and collaboration.

Lines in the Sand:
– Safe**:** preventing harmful content;
– Ethical**:** protecting user data;
– Transparent**:** ensuring access to information about how the technology works;
– Human-centered**:** avoiding the undermining of human agency and interpersonal relationships.

These principles, much like the AI Act, establish the framework within which AI-based technologies should be developed. At the same time, they indicate what kinds of solutions should be sought and what aspects deserve attention when implementing projects that integrate generative artificial intelligence into research and teaching practice.

Summary of Chapter 2

The analyses presented in this chapter portray learning as both a phenomenon and a dynamic, multidimensional process. The reference to Kolb's and Resnick's models has revealed that learning is not limited to the linear acquisition of knowledge but is instead based on cyclicality, reflection, and the processing of experience. In this sense, the learning process finds its equivalent in research practice, which likewise develops through a recurring rhythm of questions, methods, and verification.

Introducing the competence-based perspective has shown that development in the field of generative artificial intelligence cannot be reduced to acquiring technical proficiency; it requires a broader reflection on transversal competences. The model of transversal competences indicates that critical thinking, creativity, communication, and collaboration are essential for the effective and responsible use of new technologies. These competences do not exist in isolation but are interrelated and mutually reinforcing, confirming their systemic nature.

The SAMR model has made it possible to demonstrate that the use of generative AI in research and education is progressive and that its level of application depends on the researcher's competence development. At the basic levels, the tool serves a supporting and complementary function, whereas with the advancement of competences, it enables the redefinition of research and teaching practices. In this context, AI becomes a resource whose value depends on the researcher's ability for critical reflection, creative experimentation, and conscious management of cognitive processes.

This development can lead to the creation of human–machine synergy. Such synergy consists of the mutual complementarity of human cognitive, social, and ethical competences with the computational and generative potential of AI. Learning and competence development thus become prerequisites for meaningful collaboration one that does not reduce the human to a passive user but instead makes them an active co-creator. Ethical considerations are an inseparable element of this synergy, reminding us that building a research practice based on AI requires not only technical and cognitive proficiency but also responsibility, awareness of consequences, and concern for the common good.

Understood in this way, the interconnection of knowledge, competences, and technology opens a path for young researchers toward creative and meaningful scientific practice, in which generative artificial intelligence becomes an active agent in deepening thought and understanding rather than a substitute for them.

3. Limitations and Risks of Using AI in Scientific Work

The rapid development of artificial intelligence in science brings not only benefits but also a range of challenges that demand a conscious and critical approach. The use of generative models entails risks such as hallucinations, incorrect citations, data bias, as well as ethical and legal issues. This chapter discusses the main threats accompanying the integration of AI into the research process, indicating both their sources and potential consequences for scientific integrity and the credibility of publications.

3.1. Hallucinations and Bias

Generative AI especially large language models (LLMs) increasingly supports text writing, literature reviews, data analysis, and experiment design. Productivity gains are tangible (Khalifa & Albadawy, 2024), but risks to scientific integrity require strict control, particularly regarding hallucinations (fabrication of facts) and bias (Mittelstadt, Russell, & Wachter, 2023; Ferrara, 2023).

LLMs can produce fluent and stylistically correct text that may be factually incorrect. Instances of fabricated facts and fictitious citations referring to non-existent works or distorted bibliographic data have been documented (Alkaissi & McFarlane, 2023; Walters & Wilder, 2023). Hallucinations are particularly dangerous in summaries and mini-reviews, where a model may overgeneralize findings or express unjustified certainty. Therefore, LLMs should be used mainly as linguistic and editorial assistants for paraphrasing or translation not as autonomous sources of knowledge (Mittelstadt et al., 2023). Consequently, all facts and references must be verified in catalogues and databases (DOI, journal title, year, etc.).

When AI tools are involved in research, the extent of their use should be disclosed, and a critical evaluation of the content must be maintained (Alkaissi & McFarlane, 2023; Walters & Wilder, 2023).

Bias may arise from training data for example, the overrepresentation of the English language, specific regions, model architectures, or policy constraints. The result is distortion, favoritism toward certain paradigms, neglect of minority perspectives, and reinforcement of stereotypes (Ferrara, 2023). In writing and literature reviews, this may manifest as Anglocentric selections, dominance of high-impact journals, and excessive confirmation of consensus (Ferrara, 2023).

In data analysis and experimental support, bias leads to systematic model errors and design decisions that perpetuate dominant paradigms (Ferrara, 2023). Therefore, it is important to ensure diverse sources (languages, regions, research schools), test models for fairness, and implement human-in-the-loop supervision at critical stages (Ferrara, 2023; Mittelstadt et al., 2023).

"Black-box" models hinder interpretability and may overfit to patterns in data, weakening generalizability. LLMs and other generative models may suggest technically inadequate or ethically questionable experimental steps when lacking sufficient domain context (Mittelstadt et al., 2023).

Thus, AI methods should be combined with verification procedures such as external data validation, sensitivity analysis, documentation of data and decisions, and AI-generated suggestions should be treated as hypotheses to be tested, not as final conclusions (Khalifa & Albadawy, 2024; Mittelstadt et al., 2023).

Key operational principles related to hallucinations and bias:

1. Role of AI: Use LLMs primarily for style, paraphrasing, and translation - not for generating theses or conclusions (Mittelstadt et al., 2023).
2. Verification: Every claim and citation must be checked; bibliographies generated by AI should never be copied without verification (Walters & Wilder, 2023; Alkaissi & McFarlane, 2023).
3. Transparency: AI use should be disclosed in the methodology or acknowledgments; the author retains full responsibility (Khalifa & Albadawy, 2024).
4. Fairness and integrity: Ensure diversity of sources and test models for bias (Ferrara, 2023).
5. Oversight and reproducibility: Document data, parameters, and tool versions; replicate AI results using independent methods (Mittelstadt et al., 2023).

AI can enhance research productivity, but without verification rigor and bias control, it threatens scientific reliability. A critical, transparent, and responsible use with humans in the decision-making role remains the key condition for the safe integration of AI into scientific practice (Mittelstadt et al., 2023; Ferrara, 2023).

3.2. The Scale of AI-Generated Citation Errors

The widespread adoption of large language models (LLMs) in academia has brought rapid assistance for literature reviews and writing, but it has also revealed a serious problem of bibliographic hallucinations the generation of seemingly credible yet false or distorted references. LLMs operate by predicting the next likely word rather than verifying facts against source databases; hence, identification errors (e.g., DOI, PMID, volume, pages) are frequent and systematic (Alkaissi & McFarlane, 2023). This phenomenon strikes at the core of scientific integrity, as it prevents replication and verification of sources, thereby undermining trust in entire scholarly arguments (Orduña-Malea & Cabezas-Clavijo, 2023; Walters & Wilder, 2023).

The scale of the problem has been well documented in recent studies. In medicine, for example, among 115 bibliographic entries generated by an LLM, 47% were completely fabricated, 46% contained major errors, and only 7% were fully correct (Bhattacharyya et al., 2023). Another study found that over half of all references added to clinical responses were false, even though the responses themselves were sometimes partially accurate (Gravel, D'Amours-Gravel, & Osmanlliu, 2023).

Comparative analyses indicate that newer models have reduced but not eliminated hallucinations: for GPT-3.5, false citations often formed the majority, whereas for GPT-4 the proportion fell to around a dozen percent (Day, 2023; Walters & Wilder, 2023). In niche fields (e.g., specific geographic topics), particularly high concentrations of "phantom" references have been reported (Day, 2023), while in clinical radiology, only about one-third of generated sources were verifiable and appropriately supported the response (Wagner & Ertl-Wagner, 2024). Additional observations point to frequent partial hallucinations real publications cited with incorrect DOIs, PMIDs, or metadata (Athaluri et al., 2023).

Bibliometric studies describe a growing phenomenon of "ghost references" citations that appear legitimate (properly formatted author names, titles, journal names) but do not exist in any database (Orduña-Malea & Cabezas-Clavijo, 2023). The risk of their infiltration into scholarly circulation increases particularly in preprints and in publications with weaker editorial oversight. In response, new evaluation measures have been proposed such as the Reference Hallucination Score (RHS) to objectively compare tools and track progress in error reduction (Aljamaan et al., 2024).

The consequences for research practice are multidimensional. False or distorted citations introduce misinformation into literature reviews, hinder source tracing, and can even serve as an unintended "red flag" for reviewers, signaling the use of generative AI in writing (Bhattacharyya et al., 2023; Walters & Wilder, 2023). In severe cases, they may lead to manuscript corrections or retractions, causing reputational and organizational costs.

Operational recommendations (minimal protocol) for authors and editors:

- Verify the existence of each reference in independent databases (Crossref, PubMed, Scopus/Web of Science, library catalogues).
- Cross-check metadata (authors, year, title, journal, volume, pages, DOI/PMID) and confirm that the article's content matches the cited claim.
- Avoid asking LLMs for ready-made bibliographies; AI suggestions may be used only as starting points and must undergo full verification.
- Document the validation process (e.g., in supplementary materials) and apply quality indicators such as the Reference Hallucination Score (RHS) a metric assessing the authenticity and relevance of AI-generated citations to quantify hallucination risk (Aljamaan et al., 2024).
- Implement editorial reference-checking procedures, including automated DOI/PMID validation and detection of non-existent titles; in theses and dissertations, require formal verification of sources.

Using LLMs in academic work requires a defensive approach: while such tools can accelerate conceptual and linguistic tasks, the construction of bibliographic apparatus must never be delegated to generative models. Only rigorous verification of each reference can restore a minimum level of trust in the text (Alkaissi & McFarlane, 2023; Orduña-Malea & Cabezas-Clavijo, 2023; Walters & Wilder, 2023).

3.3. Ethical issues

The rapid growth of AI tools, including generative language models in research, accelerates analysis but also poses risks to scientific integrity: unclear authorship, limited model transparency, algorithmic bias, blurred accountability, and privacy concerns (Resnik & Hosseini, 2024).

Editorial and ethical consensus is clear: AI does not meet the criteria for authorship and should not be listed as a co-author, since it cannot take responsibility for content, declare conflicts of interest, or approve the final version of a manuscript (Flanagin et al., 2023; Resnik & Hosseini, 2024). The use of AI as a tool is permissible only if the scope and purpose of use are transparently disclosed (model name, type of assistance, relevant settings) a requirement now explicitly stated by an increasing number of journals (Yoo, 2025).

Authors remain fully responsible for content, including the prevention of unintentional plagiarism or AI "ghostwriting" (Flanagin et al., 2023; Resnik & Hosseini, 2024).

Advanced "black-box" models hinder reproducibility and auditability of results. Therefore, research ethics demand maximum transparency disclosure of data, protocols, metrics, and tool limitations and, where possible, the application of explainable AI (XAI) methods and documentation of model decisions (Bouhouita-Guermech et al., 2023; Resnik & Hosseini, 2024). Transparency should encompass not only how the model works, but also its role in the research process (Bouhouita-Guermech et al., 2023).

Since models learn from data, they inherit and amplify existing biases, potentially distorting conclusions and perpetuating inequities (Bouhouita-Guermech et al., 2023; Ateriya et al., 2025). Minimizing risk requires validation on diverse subsets, monitoring of fairness metrics, application of debiasing techniques, and critical review of outputs by teams with diverse expertise (Ateriya et al., 2025; Resnik & Hosseini, 2024). Ethical practice also includes ensuring equitable access to AI tools so as not to widen institutional gaps (Ateriya et al., 2025).

Accountability always lies with humans AI is neither a moral nor legal agent (Resnik & Hosseini, 2024). In practice, this means continuous human oversight, critical evaluation of AI outputs, and readiness to justify results to reviewers and the public. Editorial guidelines emphasize that authors must verify the accuracy and integrity of AI-generated content, as such content may sound authoritative yet be incorrect or biased (Yoo, 2025; Resnik & Hosseini, 2024).

Using AI services especially cloud-based ones introduces risks of leaking unpublished materials, personal data, and confidential information. Ethical use therefore requires data minimization, anonymization, careful platform selection (favoring local or institutional solutions), and clear communication with participants regarding AI involvement in the analysis of their data (Bouhouita-Guermech et al., 2023; Resnik & Hosseini, 2024).

3.4. Copyright, GDPR, and Author Responsibility

In recent years, generative AI (including ChatGPT) has rapidly entered the research workflow; however, editorial boards and ethics committees consistently require disclosure of AI use and emphasize that responsibility for content lies solely with human authors (Ganjavi et al., 2024; Hosseini, Resnik, & Holmes, 2023). The latest reviews of journal policies reveal considerable variation in editorial practices and highlight the limited reliability of AI detectors for editorial decisions hence the growing emphasis on transparency and substantive verification by authors (Yoo, 2025). Ongoing debate in the literature concerns whether accountability should be a prerequisite for authorship, yet editorial consensus remains clear: AI does not meet the criteria for authorship (Levy, 2025).

Research on LLMs shows that models can reproduce portions of their training data, including copyrighted works, in response to prompts creating a real risk of copyright infringement in academic publications (Carlini et al., 2021). Comparative studies suggest that the level of copyright compliance varies significantly across models and use cases, and that current defense mechanisms are often nonspecific (Mueller et al., 2024). For authors, this necessitates careful inspection of AI outputs for example, comparing them against sources, running plagiarism checks on generated text, and documenting the process (prompts, tool versions, scope of editing) (Carlini et al., 2021; Mueller et al., 2024).

Legal analyses emphasize that training models on copyrighted works raises concerns regarding Text and Data Mining (TDM) exceptions and transparency or licensing obligations. Both legal and academic studies point to gaps and inconsistencies in interpretation (Novelli et al., 2024; Li, 2024; Quintais, 2025). Some authors argue that training generative AI systems falls outside TDM exceptions and generally requires licensing (Dornis, 2024). In research practice, a safe strategy involves using datasets with clear licenses, avoiding the insertion of third-party copyrighted material into prompts, and including a verification and originality statement specifying the tools and versions used (Novelli et al., 2024; Li, 2024; Quintais, 2025; Dornis, 2024).

In the context of LLMs, the processing of large-scale, publicly available personal data (e.g., social media posts) for model training or deployment requires a valid legal basis; mere public accessibility does not exempt controllers from obligations under Article 6 of the GDPR (Kuru, 2024). Scholars highlight disputes over the use of legitimate interest as a lawful basis and note potential consequences for subsequent model use if the training stage was unlawful (Ruschemeier, 2025). Additional challenges arise from data subject rights (access, rectification, erasure) applied to systems that are technically difficult to "unlearn."

The literature recommends a combination of organizational and technical measures such as logging input data and limiting the inclusion of personal information in prompts (Ruschemeier, 2025; Kuru, 2024).

Reviews also point to the usefulness of privacy-preserving techniques in generative AI such as differential privacy, federated learning, secure multi-party computation (SMC), and homomorphic encryption though these approaches involve clear trade-offs in quality and cost (Feretzakis et al., 2024). For research teams, the practical minimum includes conducting a Data Protection Impact Assessment (DPIA) for projects involving personal data, minimizing data in prompts, controlling access to logs and models, and providing clear privacy information to study participants (Feretzakis et al., 2024).

Analyses of top-tier journal policies show that nearly all prohibit listing AI as an author and require disclosure of AI tool usage, often specifying the model's name, version, scope, and location of disclosure (e.g., Methods, Acknowledgments, or cover letter) (Ganjavi et al., 2024; Yoo, 2025). Ethical frameworks emphasize the authors' obligation to critically evaluate AI's contribution, describe its limitations and risks, and ensure the absence of plagiarism (Hosseini et al., 2023; Resnik, 2024). At the same time, empirical research documents frequent hallucinations and false citations, making human verification of bibliographies mandatory (Chelli et al., 2024; Farquhar et al., 2024).

Summary of Chapter 3

The aspects discussed in this chapter indicate that the use of artificial intelligence in scientific research demands caution and rigorous control procedures. While AI can effectively support researchers, it also introduces serious risks from content hallucinations and false citations to ethical, legal, and data protection violations. The key to safe AI integration lies in critical verification of results, transparency in disclosing AI use, and maintaining full human accountability. Only under these conditions can the potential of AI be harnessed without undermining the foundations of scientific integrity.

4. Methodological Changes with AI and Future Directions

The development of artificial intelligence increasingly influences research methodology, transforming how knowledge is searched for, analyzed, and presented. AI now supports not only individual tasks but also shapes new approaches to literature reviews, research design, and peer review processes. This section discusses how generative AI is reshaping traditional research practices and what future directions can be expected in the coming years.

4.1. Methodological Changes in Literature Reviews Using AI

Generative AI not only accelerates research work but also changes patterns of knowledge production from literature search and synthesis to article writing and peer-review practices. The shift involves moving from isolated, episodic tasks to integrated and dynamic processes, where humans lead and AI systems assist with planning, quality control, and continuous updating. Authors of recent handbooks and methodological reviews emphasize that effective and ethical implementation of AI requires transparency, critical evaluation of results, and full author responsibility for the integrity of the work (Haber, Jemielniak, Kurasiński, & Przegalińska, 2025; Cheng, Calhoun, & Reedy, 2025).

The literature review is becoming a continuous, semi-automated process. Editors and researchers highlight the need for dynamic reviews, updated as new data emerges and supported by AI tools for extraction, clustering, and summarization while substantive decisions remain in human hands (Tomczyk, Brüggemann, & Vrontis, 2024).

Comparative evidence demonstrates both the potential and limitations of LLMs in systematic reviews. Studies comparing ChatGPT outputs with Google Scholar results show broad topical coverage but also factual instability and hallucination risks, confirming the need for source verification and expert oversight (Tomczyk, Brüggemann, Mergner, & Petrescu, 2024).

In practice, the new methodology integrates three layers:

1. AI-assisted searching and clustering of publications,
2. Manual evaluation of quality and relevance,
3. Recorded decision pathways and update tracking.

Scientific manuals on AI in research recommend iterative verification of content and citations, comparison of summaries from multiple models, and above all careful organization and validation of bibliographies before publication (Haber, Jemielniak, Kurasiński, & Przegalińska, 2025).

At the same time, ethical guidelines and checklists are gaining importance. Cheng, Calhoun, and Reedy (2025) propose a practical set of control questions for authors regarding intellectual contribution, research competence, content reliability, and AI disclosure useful both in planning and reporting stages.

Methodological analysis is complemented by science mapping, i.e., the visualization of variables and relationships among research domains. Supported by algorithms, such mapping increases transparency in conceptual frameworks and inclusion criteria within reviews (Tomczyk, Brüggemann, & Paul, 2024).

In popular science and management literature, emphasis is placed on co-creation and democratization open repositories, interdisciplinary collaboration, and the combination of human insight with large-scale data processing promoting more inclusive and up-to-date syntheses (Przegalińska & Triantoro, 2021; Przegalińska & Jemielniak, 2023).

Finally, broader analyses of AI in academia highlight that the transformation of literature reviews represents part of a deeper epistemic shift: tools are becoming co-creators of the research process, while methodological and interpretive responsibility remains with scientists (Beshr, Ateeq, Ateeq, & Alaghbari, 2025).

4.2. Future Directions in Writing and Peer Review

In academic writing and publishing, the emerging model is that of an "editorial assistant" a system that supports structure, style refinement, journal compliance, and even simulates reviewer perspectives. Nonetheless, quality control, originality, and authorship decisions remain strictly human (Haber, Jemielniak, Kurasiński, & Przegalińska, 2025).

The institutional framework of this trend is being shaped by rapidly evolving guidelines based on principles of AI transparency, author accountability, and continuous policy updates aligned with technological progress. Such frameworks, developed by research teams and academic organizations, emphasize human oversight, transparency, and process safety (Bockting, van Dis, van Rooij, Zuidema, & Bollen, 2023).

Recommendations for writing with AI in medical journals specify two practices that are quickly becoming standard:

1. AI tools should not be listed as co-authors, and

2. The exact nature of AI use should be disclosed in the Methods section or Acknowledgments, accompanied by a warning about fabricated citations and factual errors (Cheng, Calhoun, & Reedy, 2025).

In peer review and evaluation from literature assessment to grant reviews AI will continue to support screening, summarization, and ethical risk detection, but will not replace expert judgment. Scholars emphasize potential model biases, the necessity of full human control, and the need for transparent review procedures (Haber, Jemielniak, Kurasiński, & Przegalińska, 2025).

In the short term, further development of dynamic reviews and automation of technical stages can be expected, along with higher reporting standards from decision-tracking logs to prompt documentation. Conceptual contributions to these hybrid practices, combining automation with rigor, are exemplified by works on science mapping and interdisciplinary methodological standards (Tomczyk, Petrescu, Falco, & Alola, 2024).

The medium-term direction points toward distributed, co-created publishing environments, where authors collaborate with intelligent writing agents and institutions adopt human-in-the-loop policies. Both management and popular science literature describe this shift as a move from “efficiency” to “co-creation,” provided that accountability, transparency, and originality are maintained (Przegalińska & Jemielniak, 2023; Przegalińska & Triantoro, 2021).

On the horizon, we can also expect an expansion of multimodality (text–data–image), integration with open science, and increased evidentiary standards for models (explainability, traceability). The future will likely involve greater professionalization of practices, mandatory originality checks, cross-verification of citations in scholarly databases, and AI literacy training for both authors and reviewers (Haber, Jemielniak, Kurasiński, & Przegalińska, 2025).

The future of writing and reviewing is not about automating judgment but about enhancing the scientific process. Successful practices will combine automation of labor-intensive stages with rigorous expert evaluation, transparency, and evolving standards. This is precisely the direction taken by initiatives promoting dynamic reviews, ethical guidelines, and hybrid synthesis methodologies (Tomczyk, Brüggemann, & Vrontis, 2024; Beshr, Ateeq, Ateeq, & Alaghbari, 2025).

Summary of Chapter 4

The examples discussed in this chapter indicate that artificial intelligence is becoming an integral component of modern research methodology introducing dynamic literature reviews, automation of selected research stages, and new forms of collaboration between authors and reviewers. Its role is not to replace researchers but to enhance creative and analytical processes, provided that responsibility and transparency are maintained. Future directions include broader use of multimodal models, integration with open science, and increasing demands for AI explainability and transparency in all stages of scholarly work.

5. Scientific Publishing Policies and Legal Issues

The rapid adoption of generative artificial intelligence tools has prompted academic publishers and institutions to establish detailed regulations governing their use. These policies address issues such as authorship, transparency, copyright protection, publication ethics, and the use of AI in the peer-review process. This chapter presents the positions of major publishers and key legal frameworks shaping the rules for using AI in academia, highlighting both their diversity and shared minimum standards.

5.1. Positions of Leading Academic Publishers and Journals

The policies of major publishers regarding generative AI vary widely from conservative approaches that limit AI use to language editing, to more open ones that allow assistance in writing or analysis under full author accountability. Despite differences in detail for example, in disclosure thresholds or exceptions for AI-related research a clear common canon emerges:

- AI cannot be listed as an author;
- Significant AI use must be transparently disclosed;
- Manipulation of images or data and delegating substantive evaluation of manuscripts to AI are strictly prohibited.

These policies are rapidly evolving, and therefore it is always necessary to consult the most recent guidelines of a specific publisher or journal.

Elsevier allows the use of generative AI tools only to improve readability and language, provided that authors retain full control over the content and bear complete responsibility for the material, as summarized in Table 1. Explicit disclosure of AI use is required in a dedicated section of the manuscript if any tool contributed to text editing. However, AI cannot be listed as an author or co-author, as it does not meet the criteria of accountability for the content.

Regarding illustrative materials, Elsevier prohibits the creation or modification of scientific images using generative AI, except when such use is itself the subject of the study and is transparently described in the Methods section, with original files available upon request.

In the peer-review and editorial process, Elsevier explicitly bans the use of tools such as ChatGPT for manuscript assessment; peer review must remain fully human, although the publisher is exploring compliant, policy-aligned assistive solutions.

Table 5.1. Summary of Key Principles in Elsevier's Policy on Generative AI

Is it permissible to use generative AI in writing text?	**Is disclosure of AI use required?**	**Can AI be listed as an author/co-author?**	**Policy regarding AI-generated images/figures**	**Peer review policy and/or other comments**
Yes, but only to improve readability and language. Use only under human supervision (the author bears full responsibility).	Yes. You should include a statement in a separate section if you used AI for writing.	No. AI cannot be a co-author because it does not meet the criteria for responsibilit y for content.	Prohibition on the use of generative AI to create or modify scientific images. The only exception is when it is part of the research project itself in which case it must be described in the methods and the original files may be required.	Reviewers and editors: the use of ChatGPT-type tools for reviewing is prohibited; Elsevier is working on evaluating AI solutions that comply with its policy, but for now, reviewing is to be done entirely by humans.

Source: own study based on Elsevier's policy (date: 04.2025)

Springer Nature allows the use of AI as a linguistic support tool or an analytical aid, while maintaining the author's full responsibility for the content. Based on the summary in Table 2, it is worth noting that for more advanced applications such as generating text fragments it is necessary to disclose this in the methodology section or another appropriate part of the article. Simple language correction does not always require such a declaration. AI cannot be credited as an author. Regarding illustrations, the creation of generative images is prohibited unless it directly results from the research project, provided that data verifiability and copyright compliance are ensured. In the review process, the publisher asks reviewers not to upload manuscripts to AI tools due to confidentiality concerns. If any AI assistance has been used, it must be disclosed to ensure transparency of the process.

Table 5.2. Summary of key principles of Springer Nature's policy on generative AI

Is it permissible to use generative AI in writing text?	**Is disclosure of AI use required?**	**Can AI be listed as an author/co-author?**	**Policy regarding AI-generated images/figures**	**Peer review policy and/or other comments**
Yes, provided that AI tools are used for language	Yes, provided that AI tools are used for language support (or	No. AI tools do not meet	The use of generative AI to create illustrations is	Review: Springer Nature asks reviewers not to upload

support (or data analysis) and the text and responsibility still belong to the author.	data analysis) and the text and responsibility still belong to the author.	the criteria for authorship; the author must be fully responsible for the content.	prohibited. Only in strictly defined exceptions (when it is part of AI research, and the data is verifiable and copyright is respected).	manuscripts to AI tools (concerns about confidentiality and reliability). If a reviewer has used AI in any way to evaluate research, they should disclose this.

Source: Author's own elaboration based on the Taylor & Francis generative AI policy (date: April 2025)

Based on the summary in Table 3, it can be stated that Taylor & Francis allows the use of AI as author support for idea generation, writing assistance, and language improvement, with full scholarly responsibility resting with the authors. A clear statement specifying which tool was used and for what purpose is required, either in the methodology section or in the acknowledgements. AI cannot be listed as an author. The publisher explicitly prohibits the creation or manipulation of images and data intended for publication (e.g., adding or removing elements), as this is considered a violation of editorial principles. During the peer review process, editors and reviewers are not allowed to upload materials to AI tools due to confidentiality and intellectual property risks. Only minor linguistic "polishing" of reviews is permitted, provided full responsibility and confidentiality are maintained.

Table 5.3. Summary of key principles of Taylor & Francis's policy on generative AI

Is it permissible to use generative AI in writing text?	**Is disclosure of AI use required?**	**Can AI be listed as an author/co-author?**	**Policy regarding AI-generated images/figures**	**Peer review policy and/or other comments**
Yes, but limited to supporting the author, e.g., in generating ideas, facilitating writing, and improving language. The author remains fully responsible for accuracy and correctness.	Yes. It is necessary to clearly state which tool was used and for what purpose (e.g., in the Methods or Acknowledgments section).	No. AI cannot be an author. Authors must be human beings (legal and substantive responsibility).	It is prohibited to use AI to create and manipulate images and data for publication (e.g., removing or adding elements). This violates the T&F rules.	Review: Editors and reviewers cannot upload materials to AI tools (risk of intellectual property and confidentiality violations). Reviewers may use AI to improve the language of their reviews, but they remain fully responsible for the content and confidentiality.

Source: Author's own elaboration based on the Taylor & Francis generative AI policy (date: April 2025)

Wiley treats AI solely as a supportive tool. Authors must retain full control over the entire text and are responsible for its scholarly accuracy and proper citation, as indicated in Table 4. Disclosure of AI use is mandatory in the methodology section or acknowledgements if it has influenced the content beyond simple spelling or grammar correction. AI cannot be credited as an author this rule is additionally grounded in the COPE (Committee on Publication Ethics) guidelines. In terms of images and data, the generation or manipulation of results is prohibited. Only minor technical adjustments such as sharpening or color correction are allowed, provided they do not distort the data. During peer review, AI tools may be used to improve the language of the review itself, but entire manuscripts must not be uploaded. Any AI assistance must be disclosed to ensure confidentiality and transparency.

Table 5.4. Summary of key principles of Wiley's policy on generative AI

Is it permissible to use generative AI in writing text?	**Is disclosure of AI use required?**	**Can AI be listed as an author/co-author?**	**Policy regarding AI-generated images/figures**	**Peer review policy and/or other comments**
Yes, but only as a supporting tool. Authors must retain control and responsibility for the entire text, including factual accuracy and citations.	Yes. It is essential to disclose in the Methods/Acknowledgments section if AI has influenced the content (beyond simple spelling/grammar correction).	No. Wiley also refers to COPE guidelines in this regard. AI cannot hold copyright or act as a conscious author.	Generating or manipulating original research data or results using AI is not permitted. With regard to images, Wiley does not allow the "creation" of results. However, correction tools (e.g., color correction in illustrations) are permitted as long as they do not falsify data.	Review: Wiley suggests that reviewers/editors may use AI to improve the language of reviews, but entire manuscripts must not be uploaded to AI (confidentiality protection). It must be disclosed if AI was involved in the creation of the review.

Source: Author's own elaboration based on the Wiley generative AI policy (date: April 2025)

SAGE permits the use of tools for style and language correction generally without the need for disclosure. However, generative use of AI i.e., creating actual portions of a publication must be declared, including the model used and its purpose. AI cannot be credited as an author. The publisher emphasizes the author's responsibility to verify information in order to avoid hallucinations and incorrect citations. Regarding illustrations, it is prohibited to generate images depicting data, experimental results, or other key elements of the work. Any use of AI in the creation of illustrations must be disclosed, and the editorial team reserves the right to reject materials if their reliability is in doubt. In the review process, SAGE prohibits the generation of reviews using AI tools due to confidentiality concerns, allowing only language editing tools for stylistic improvement.

Table 5.5. Summary of key principles of SAGE's policy on generative AI

Is it permissible to use generative AI in writing text?	Is disclosure of AI use required?	Can AI be listed as an author/co-author?	Policy regarding AI-generated images/figures	Peer review policy and/or other comments
Yes, in terms of writing assistance, e.g., tools for style and language correction (without the need for disclosure). However, the use of generative AI (e.g., ChatGPT) to create actual fragments of publications must be disclosed.	Yes, in cases where AI generated text fragments, data, or other content. You must indicate which model was used and for what purpose.	No. AI cannot be credited as the author. You must ensure the originality of the content and verify the information generated by AI (e.g., avoiding "hallucinations" and errors in citations).	Generating images is prohibited if it serves to present data, experimental results, or other key elements of the publication. Any use of AI tools to create illustrations must be disclosed, with the proviso that SAGE may reject them if there are doubts about their reliability.	Review: SAGE prohibits the use of generative AI to create reviews (breach of confidentiality). It allows the use of tools for linguistic correction of reviews. If an editor suspects misuse of AI (e.g., in the text), they may reject the submission.

Source: Author's own elaboration based on the SAGE generative AI policy (date: April 2025)

As shown in Table 6, the IEEE (Institute of Electrical and Electronics Engineers) allows the use of AI in writing, provided that full human responsibility for the content is maintained. Authors are required to clearly indicate which sections of the article include AI-generated material, with an acknowledgment included in the "Acknowledgements" section. AI cannot be listed as an author or assume any legal or ethical responsibility. The same level of transparency is required when generating images or source codes, though manipulation of key data is strictly prohibited. In the peer review process, uploading entire manuscripts to AI tools is not permitted. If AI is used solely to improve the language of a review, this should be disclosed to ensure transparency and protect confidentiality.

Table 5.6. Summary of key principles of IEEE's policy on generative AI

Is it permissible to use generative AI in writing text?	Is disclosure of AI use required?	Can AI be listed as an author/co-author?	Policy regarding AI-generated images/figures	Peer review policy and/or other comments
Yes, AI can be used in writing, but full human responsibility is necessary.	Yes. IEEE requires explicit disclosure and indication of the sections of the article where AI-generated content has been used. This should be mentioned in the Acknowledgments section.	No. AI cannot be considered an author, nor can it assume legal and ethical responsibility.	Similar disclosure is required if images or source codes, among other things, were generated. There is no open consent to manipulate key data using AI.	Review: No formal permission to upload entire manuscripts to AI tools. If AI has been used, for example, to improve the language of a review, it is recommended that this fact be disclosed in order to maintain transparency and confidentiality of the process.

Source: Author's own elaboration based on the IEEE generative AI policy (date: April 2025)

Emerald permits the use of AI for language support and text improvement; however, any new content created by AI must be disclosed, and authors bear full responsibility for its accuracy and integrity, as summarized in Table 7. AI cannot be listed as an author. In graphical materials, the publisher prohibits the submission of images entirely generated by AI. It is also not recommended to generate substantial portions of the article without thorough author verification. During the peer review process, editors and reviewers are not allowed to use generative AI tools to process manuscripts or make editorial decisions. Emerald's policy explicitly forbids such applications within the peer review procedure.

Table 5.7. Summary of key principles of Emerald's policy on generative AI

Is it permissible to use generative AI in writing text?	Is disclosure of AI use required?	Can AI be listed as an author/co-author?	Policy regarding AI-generated images/figures	Peer review policy and/or other comments
Yes, but limited to language support and text improvement. Any new content created by AI must be disclosed. The author is fully responsible for accuracy.	Yes, the author must declare the use of generative tools in the article/chapter. The policy is effective from the moment of announcement.	No. AI cannot be an author (no possibility of liability). Authors are required to cite sources and maintain the integrity of the text.	It is prohibited to submit images created entirely by AI for publication. It is also inadvisable to generate entire sections of an article that are not verified by the author.	Review: Editors and reviewers cannot use generative tools to process articles and decide on publication (confidentiality, risk of rights infringement). Emerald explicitly prohibits the use of AI in the review process.

Source: Author's own elaboration based on the Emerald generative AI policy (date: April 2025)

On a comparative scale, Elsevier and Emerald are among the more restrictive publishers, allowing the use of AI mainly for language and stylistic correction, while Springer Nature, Taylor & Francis, Wiley, SAGE, and IEEE permit slightly broader support such as preliminary analysis or editorial assistance provided that the author assumes full responsibility and explicitly discloses the use of AI in creative sections.

The common minimum standards across all publishers include:

1. Transparency obligation: disclosure of AI use whenever the tool contributes to the creation of content or illustrations. Simple language correction is sometimes exempt from this requirement (e.g., SAGE, Springer).
2. Clear refusal to grant authorship to AI: no exceptions allowed.

3. Caution regarding images and data: a universal ban on generating or modifying materials that could distort results. Elsevier and Springer explicitly prohibit the generation of scientific images except in well-documented research contexts related to AI itself, while Wiley allows only minor technical adjustments.
4. Strict rules in peer review: no permission to use AI for substantive evaluation or to upload manuscripts into AI tools, with only limited acceptance of simple linguistic corrections in reviews subject to mandatory disclosure.

In the case of Polish journals and publishers, formal and detailed AI guidelines are still often lacking. The practical minimum remains the substantive justification of AI use and full transparency toward editors and readers.

However, exceptions establishing clear standards are increasingly emerging. For example, the Journal of Modern Science has adopted a comprehensive AI policy requiring precise disclosure (including tool name, model, version, date of use, and prompt content). AI may only be used for language correction, stylistic improvement, and translation. The generation of substantive content or data is prohibited, and AI cannot be credited as an author.

Regarding illustrations, the creation or modification of images using AI is forbidden except when it forms part of a documented research methodology. Only charts generated from author-prepared data are allowed, with AI treated as a graphical tool and its use noted in the article.

The policy also extends to reviewers and editors: strict confidentiality of materials and correspondence, prohibition on uploading manuscripts or reports to AI tools, and full human responsibility for evaluations and decisions. Undisclosed AI use may result in manuscript rejection, and the editorial office reserves the right to detect AI involvement using *Plagiat.pl* (Journal of Modern Science).

Such measures bring national publishing practices closer to the global standards of transparency and accountability and may serve as a model for developing local policies.

Taken together, these policies establish a coherent standard: AI may support authors as a linguistic or editorial aid, but it cannot replace the author, create or modify research results, and any use beyond language correction must be openly disclosed and verifiable.

5.2. Authorship Criteria and AI Use; Transparency Declarations

The issue of authorship in academia is not limited to the formal attribution of names to the creators of a given scientific publication. It has always been inherently connected with responsibility for the content, integrity, and openness to engage in critical discussion regarding the presented findings.

With the emergence of generative artificial intelligence tools, new challenges have arisen in this area. The fundamental question concerns how to interpret the contribution of technology in the research process and how to avoid attributing to it qualities traditionally reserved for human authors.

According to the position of the Committee on Publication Ethics (COPE), artificial intelligence cannot be recognized as an author, as it fails to meet essential authorship criteria such as the ability to make conscious decisions, assume responsibility, or respond to the peer review process (COPE, 2023). Similarly, the license terms of major generative AI providers explicitly state that authorship cannot be attributed to the technology.

Table 5.8. Summary of copyright aspects related to content generated using generative AI

Company / Tool	Status of authorship of AI-generated content	Key provisions/practices
OpenAI – ChatGPT	Content authorship attributed to the user. OpenAI emphasizes that it does not claim any rights to the Output.	The user retains rights to Input and Output; OpenAI may use the data for training purposes unless the user disables this in the settings. (OpenAI, 2025)
Microsoft – Copilot	Content authorship attributed to the customer/user. Microsoft declares that it does not assume copyright.	Microsoft undertakes to defend users against claims of copyright infringement if they use the software in accordance with the recommendations and filters. (Microsoft, 2023)
Google – Gemini	Authorship treated as belonging to the user, with a strong emphasis on transparency (indicating that the content comes from AI).	The user retains the rights to the content, but Google reserves the right to use it to improve its services; it uses tagging tools. (Google, 2024)
Anthropic – Claude	Content authorship attributed to the user. Claude acts as a supporting tool, not a copyright holder.	The user has rights to the output data, but Anthropic reserves that it is not liable for any third-party claims arising from infringement of rights. (Anthropic, 2023)

Source: own study based on the policies of OpenAI, Google, Microsoft, and Antropic model creators

When we examine one of the leading players in the generative AI market OpenAI we find that the issue of authorship is regulated in a relatively transparent manner. According to the current rules, the user retains full rights to both the content entered into the system (input) and the content generated by the model (output). OpenAI explicitly states that it does not claim copyright over users' generated outputs, reserving only the requirement to comply with applicable laws (e.g., personal data protection and privacy rights) and its own internal regulations.

For this reason, regardless of the tool chosen, it is important for early-career researchers to interpret authorship from the perspective of copyright law, institutional guidelines, publishing policies, and academic ethics.

An important aspect of copyright concerns the sharing of one's own resources or works (within the meaning of copyright law), for example through personalized GPTs. When such resources are made publicly available in the GPT Store, the content creator grants OpenAI a non-exclusive, worldwide, irrevocable, royalty-free license to use, store, modify, distribute, and promote the created materials. This means that the act of creation within the OpenAI environment can be divided into private and public spheres. In the private sphere, OpenAI's regulations guarantee the confidentiality of conversations and projects.

From the perspective of authorship criteria, the key distinction lies between the human creative act and the functioning of the model. OpenAI emphasizes that although the user acquires copyright to the generated material, they cannot be regarded as the sole author in the traditional sense. The algorithm serves as a tool that participates in the creative process but cannot, by its nature, be a legal subject of authorship. In practice, authorship depends on the degree of original human contribution through prompt formulation, editing, and interpretation of the generated output. Authorship in the AI context is therefore processual and relational, rather than individualistic and closed.

Consequently, generative AI tools should be regarded as supportive instruments, and their use must be explicitly declared. Transparency in this sense involves specifying the scope, purpose, and nature of use whether for linguistic editing, analytical assistance, or visualization generation.

This obligation to ensure transparency is also grounded in Polish research ethics frameworks. The Code of Ethics for Researchers of the Polish Academy of Sciences (PAN, 2024), in paragraph 16, explicitly states that every contribution to a scientific work should be honestly and transparently described, and that full responsibility for the publication rests solely with its authors. In light of these principles and interpretations, there is no basis for attributing authorship to technology, which lacks agency and moral responsibility (PAN, 2024).

A similar position is taken by national initiatives promoting education and digital competence development. The guidelines prepared by the Center for Modern Education at Gdańsk University of Technology, led by Prof. Joanna Mytnik, emphasize that generative tools can support both research and teaching processes, but their use must be disclosed in a way that allows evaluation of the author's actual contribution. Transparency thus becomes a safeguard ensuring not only research integrity but also clarity in the education of young scholars (CNE, 2023).

Given these developments, it is worth stressing that the future of scientific work requires a balance between harnessing AI's potential and preserving the central role of the researcher. Authorship remains inseparable from responsibility, and transparency declarations serve a protective function strengthening trust and integrity within the academic community. For early-career researchers, this means building a research practice grounded in ethical awareness and reflective collaboration between humans and technology.

5.3. Copyright to the text and licensing models

Copyright law not only within the field of academic work is a complex and multi-layered issue, one that is difficult to fully address even in an extensive publication. Therefore, this subsection includes the topic of open licenses, which originated before the popularization of generative AI models but remains universal, relevant, and worthy of further development and support for reasons of clarity, accessibility, and ethical consistency.

It is important to note that the issue of authorship in the digital world extends far beyond the internal regulations of generative AI service providers. Since the beginning of the 21st century, Creative Commons (CC) licenses have played a crucial role in organizing and standardizing the domain of open resources. They emerged as a practical response to the growing need for a clear and internationally comprehensible framework for defining the conditions under which creative works can be used. Thanks to CC licensing, it became possible to build a global trust infrastructure a system in which creators can consciously share their work, and users can confidently understand the permissible scope of its use.

Contemporary publishing practices increasingly combine the rigor of traditional legal protection models with the open-access philosophy, for which Creative Commons licenses have become the central instrument. Their significance in the academic context lies in the fact that they allow authors to retain moral and intellectual property rights while enabling various degrees of open use by other researchers and institutions.

The CC licensing system comprises several variants that differ in the level of permissions granted to users:

- CC BY allows unrestricted use of a work, provided proper attribution is given to the author. This license is one of the most common in academic publishing, as it maximizes dissemination and citation potential.

- CC BY-SA (ShareAlike) adds the requirement that derivative works be distributed under the same license, reinforcing a culture of collaboration and knowledge sharing.
- More restrictive variants, such as CC BY-NC (non-commercial use only) or CC BY-ND (no derivatives), limit flexibility especially in research and educational contexts by prohibiting commercial use or the creation of adaptations.

5.4. Licensing tool customization

The emergence of generative artificial intelligence has significantly complicated this previously stable framework. Language models have been trained on massive datasets in which questions of authorship and licensing conditions were largely overlooked particularly during the early stages of technological development. This means that the very foundations of openness, reciprocity, respect for rights, and transparency have, in practice, been suspended.

In this context, Creative Commons, as a movement that has long provided ethical foundations for open culture, may once again serve as a point of reference and a source of solutions for new challenges.

One such response is the CC Signals initiative, introduced in 2025 as an attempt to create a "new social contract for the AI era" (Creative Commons, 2025). Signals take the form of a socio-technical standard that enables creators and institutions to express their preferences regarding how their works may be used by artificial intelligence systems both during training and in subsequent distribution. The main goal of CC Signals is to preserve the spirit of Creative Commons simplicity, accessibility, and global usability while adapting it to the realities of machine learning. Importantly, this solution does not reject earlier CC frameworks but rather extends them, building a bridge between openness and responsible data use in the age of generative AI.

In this way, Creative Commons can continue to serve as an ethical regulator of the open resources ecosystem, now encompassing artificial intelligence as well. CC Signals preserve core values transparency, reciprocity, and respect for creativity while expanding them to address the rapidly evolving technological environment. They thus represent a practical example of how well-established, tested principles can be reinterpreted to meet global needs while remaining accessible to the entire international community.

Alongside open licenses, other licensing models are also used in academic publishing. Commercial publishers often require authors to transfer full economic rights to them, resulting in a loss of control over how their work is shared. Increasingly, hybrid models are emerging, allowing authors to choose between traditional closed-access publication and open access, typically subject to a publication fee. Of particular importance are publishing licenses based on the Gold Open Access model, which ensures full openness under CC BY terms, and the Green Open Access model, which allows self-archiving of the manuscript version in institutional repositories.

From the perspective of early-career researchers, it is essential to understand that the choice of license is not merely a technical matter, but one that determines how their work participates in the circulation of knowledge and contributes to the body of scientific resources. Open licenses increase the visibility of publications, support international collaboration, and facilitate the creation of synergies among researchers. However, they also require legal awareness and responsibility to ensure that shared content does not infringe upon the rights of others.

Summary of Chapter 5

The analysis of publishing policies and legal regulations shows that, although individual institutions differ in their approaches to AI use, all emphasize the need for transparency, prohibit recognizing AI models as authors, and reaffirm the researcher's responsibility for content. Copyright, data protection, and compliance with frameworks such as the GDPR and the AI Act are gaining increasing importance.

The future of scholarly publishing will depend on balancing openness to innovation with strong ethical and legal safeguards, ensuring the integrity of the scientific process while fostering responsible and transparent collaboration between humans and intelligent technologies.

Part II Practical Guide

The second part of the monograph focuses on the practical dimension of using artificial intelligence in academic work. While the theoretical section presented the fundamental concepts, definitions, and ethical–legal contexts, this part concentrates on specific tools, techniques, and scenarios for their application. The proposed solutions cover both support in writing and editing texts and the automation of auxiliary tasks, literature analysis, and verification of content generated by language models.

The aim of this part is to provide doctoral students and young researchers with a set of practical guidelines that enable them to consciously and responsibly integrate AI tools into their own research practice, while maintaining critical reflection and quality control of the outcomes.

6. Prompt Engineering

This chapter focuses on the practical aspects of using generative artificial intelligence in the work of a young researcher. Recalling the definitions, concepts, and perspectives presented in the first part, the reader is encouraged to engage in hands-on exploration of AI tools, to seek individual pathways, and to develop personal competences.

Among the many available tools, one can find ChatGPT, Gemini, Copilot, Claude, NotebookLM, as well as Polish models such as Bielik or PLLuM. Although the list of tools is much longer and new solutions or updated versions appear daily the principles and techniques of working with them remain universal. This means that experience gained with one tool can be transferred and successfully applied in other environments.

The method of working with generative AI that enables the creation of meaningful content through carefully designed instructions in natural language is known as prompt engineering. "Prompt engineering is an essential technique that extends the capabilities of large language models (LLMs) and vision–language models (VLMs). It involves the strategic design of task-specific instructions, called prompts, to guide the model's output without modifying its underlying parameters." (Sahoo et al., 2024)

The main aspects of prompt engineering include (Sahoo et al., 2024):
– Enhancing model effectiveness – prompts enable seamless integration of pre-trained models with new tasks, eliciting desired model behaviors based solely on the provided instruction.
– Types of prompts – these may include natural language instructions that provide context to steer the model, or learned vector representations that activate relevant knowledge.

– Adaptability – prompt engineering offers a mechanism for fine-tuning model outputs through carefully crafted instructions, allowing models to perform effectively across diverse tasks and domains. This flexibility distinguishes it from traditional methods, which often require retraining or extensive parameter adjustments.

Transformative impact – prompt engineering has become a transformative force in artificial intelligence, unlocking the vast potential of LLMs and enabling them to perform tasks once thought impossible, from language generation and question answering to coding and reasoning.

An important aspect illustrating how diverse and personalized the practice of prompt engineering can be is the fact that there is no single universal prompt template that guarantees valuable and contextually appropriate results. "The contemporary landscape of prompt engineering encompasses a spectrum of techniques from fundamental methods such as zero-shot and few-shot prompting to more advanced approaches like 'chain-of-code' prompting." (Fagbohun et al., 2024)

Given the breadth of this field, young researchers must engage in continuous learning, experimentation, curiosity, and the application of their own competences, as emphasized in Chapter 1. In this way, prompt engineering techniques can become fully integrated into the broader framework of research and teaching practice.

6.1. Prompt engineering and prompt learning

In the literature on the subject, a distinction is increasingly being made between prompt engineering and prompt learning. The first of these concepts refers to the practice of manually formulating commands in natural language with the aim of obtaining a response from the model that is as precise as possible and consistent with the user's intention. It is this form of prompting that is the basic tool in the work of a young researcher, allowing them to iteratively refine instructions and control the quality of the generated results. However, the development of research on large language models has shown that not all aspects of interaction with them need to take place directly through natural language. A trend known as prompt learning has emerged, which encompasses various methods of automatically learning the prompts themselves. Solutions such as soft prompts and prefix tuning are of key importance here. In the case of soft prompts, instead of traditional words, sequences of vectors in the hidden space of the model are used, which do not correspond to any real linguistic units, but act as subtle signals guiding the generation of responses (Liu et al., 2021).

Prefix tuning, on the other hand, involves attaching learned vector prefixes to the model input, which allow the task context to be introduced and the model's behavior to be controlled without having to modify all of its parameters (Li and Liang, 2021). From a scientific practice perspective, the difference between these two approaches is significant. Prompt engineering is a tool available to every user and allows them to develop the ability to formulate precise commands. Prompt learning, on the other hand, is an area of research into how models can be adapted to specific research tasks by learning small fragments of parameters instead of fully training the model. Understanding both perspectives enables young researchers not only to consciously use the tools available in their daily work, but also to orient themselves in the directions of research into new ways of interacting with generative artificial intelligence.

6.2. The Structure of an Effective Prompting Process

Although prompts can take many different forms, there is a framework that can help navigate the world of generative AI. As presented in the course *"*Google Prompting Essentials,*"* available for example on the Coursera platform, Google engineers share the following structure of the prompting process, shown in Table 6.1.

Table 6.1. Components of the Prompting Process

Task	**Context**	**Reference**	**Evaluation**	**Iteration**
A detailed description of the goal, task format, and the role of artificial intelligence	Key information presenting the scope, analysis, and specificity of the issue and its needs	Examples, reports, and data related to the task; cultural, social, or paradigmatic background	Assessment of the generated content	Continuation of the process through filling gaps, refining, and supplementing data

Source: author's own elaboration based on *Google Prompting Essentials*

Similar components of prompting can be found in the litewhiterature on this subject. In the article by White et al. (2023), the following elements are identified, as shown in Table 6.2.

Table 6.2. Components of Prompting According to White et al.

Name and Classification	**The intent**	**The motivation**	**The structure and participants**	**Example code**	**Consequence s**

Identifies and defines the problem to be solved	Describes the problem and the objectives to be achieved	Justification of the problem or task	Fundamental contextual information	Testing the prompt's application in practice	Reflection on the advantages and disadvantages of the prompt

Source: author's own elaboration based on White et al. (2023)

W The available literature also emphasizes the importance of iteration, which is related to the continuous improvement of prompts and highlights the process-oriented nature of communication with GenAI tools (White et al., 2023; Liu et al., 2023; Fagbohun et al., 2024). Since the model developed by Google engineers is clear and consistent with scientific frameworks, let us now trace the individual stages of the prompting process and discuss each component in detail.

Task

When starting to use any LLM-based tool, the process should begin, as in project work, with defining the goal that the activity is meant to serve. The goal should be specific and clearly describe what we aim to achieve. The process of preparing instructions and conducting a conversation will look entirely different depending on whether we need feedback, language correction, a material review, data analysis support, or assistance in designing a simulation or experiment.

At this stage, we can also define what role the chatbot should assume. It can, for example, assess the readability of a text from the perspective of a beginner in a given field, or it can provide expert-level guidance in a specific discipline. Defining its role will influence what is generated during the interaction. It is also possible to specify the **form** of the response in terms of length, number of words or sentences, as well as structure (e.g., bullet points or continuous prose). The style can likewise be defined as formal, informal, popular-scientific, or academic.

Context

Generative AI tools are digital systems that rely on data to which they have access. They do not inherently infer our intentions, needs, or paradigms. When we open a chat window and ask a question, the chatbot responds using advanced statistical models based on the data on which it was trained. A short prompt causes the model to generate output grounded primarily in its training corpora (including web data), resulting in a response calibrated for the average user.

This is precisely the situation we want to avoid. By enriching the instruction with contextual details, the circumstances and background in which the responses are to be generated, we shape and guide the model's behavior (Liu, 2023). Providing our own data that defines the desired scope of the answer, the user's role, and the required perspective helps fine-tune both the style and the range of the model's responses.

Through additional guidance and reference to specific research or educational areas, we can calibrate the model's outputs so that they are more relevant, satisfactory, and aligned with our current needs.

References

Many of us possess studies, research results, or texts that are valuable to our academic or teaching practice both our own and those that have influenced our development. These are invaluable resources that strengthen and enrich the context provided to the model. Including them in the dialogue window helps narrow the scope of responses to a specific viewpoint, domain of knowledge, or analytical and synthetic style.

Additionally, when preparing a prompt, we can provide a model answer as a reference, allowing the chatbot to familiarize itself with its structure and language before generating a response aligned with that pattern. This helps adapt the form and style of generated content to the user's expectations.

Equally important are the specific databases we wish to base our work on. Indicating and verifying whether the model uses these sources correctly can improve the quality and reliability of the generated results.

Evaluate and iterate

As repeatedly emphasized throughout this publication, human competences are indispensable in working with digital systems. This stage of the prompting process represents a crucial contribution to the quality of outcomes achieved. Generated content should always be reviewed, analyzed, and critically assessed. This serves as the foundation for both further use of the material in subsequent research stages and for ensuring meaningful continuation of collaboration with the model within a given task.

Repetition and deepening of the prompting process are essential elements of professional interaction with language models. Even in the best-designed initial prompt, errors, misunderstandings, and contextual gaps inevitably appear, influencing the result. Recognizing them during evaluation and redefining needs, scope, style, and expectations is therefore indispensable.

The components of the prompting process discussed above indicate that meaningful and effective work with these tools also requires effort, engagement, and the use of one's own cognitive resources.

6.3. Prompt Engineering Techniques

Practical experience with large language models reveals that the way instructions are formulated significantly affects the quality of the generated content. The literature identifies several fundamental techniques that help researchers better understand model mechanisms and achieve results more closely aligned with their needs.

One of the simplest methods is zero-shot prompting, which involves asking a question without providing any prior examples. The researcher assumes that the model can infer intent solely from the content of the query. In practice, however, to increase response precision, few-shot prompting is often used. This approach precedes the main question with several examples of desired answers, allowing the model to grasp the pattern and adjust its subsequent output accordingly. Another technique, chain-of-thought prompting, encourages the model to present its reasoning step by step. This method is particularly useful in academic contexts, where not only the final result but also the transparency and logic of reasoning are valued (Wei et al., 2022).

Also noteworthy is role prompting, in which the model is assigned a specific role such as a journal reviewer, thesis supervisor, or lecturer. Responses generated in this mode reflect not only the content of the query but also the social or institutional context in which it is situated. Another approach, instruction-based prompting, relies on precisely formulated commands, often explicitly specifying the expected response format, for example, in the form of a table, list, or summary of a defined length.

Each of these techniques demonstrates that prompt engineering is not limited to intuitively asking questions; rather, it requires a deliberate selection of strategies appropriate to the research objective. The ability to apply them becomes an integral part of the academic toolkit akin to mastering data analysis methods or understanding the principles of sound reasoning.

6.4. Methods of Building Prompts

As indicated earlier in the section on the prompting process, the structure of a prompt can vary. Below are two approaches to constructing prompts. The structure proposed by Maciej Chrzanowski may be organized as follows (Wojewodzic, 2024, p. 22).

Table 6.3. Example Structure of a Prompt

Role	**Task**	**Task Structure**	**Context**	**Goal**	**Response Format**
Act as [...]	Describe [...] in the style of [...]	First [...], then [...]; maximum number of characters [...]	The description should be part of [...]	Your goal will be [...] and the audience is [...]	The description should take the form of [...]; in the first part [...]

Source: author's own elaboration of the prompt structure based on Maciej Chrzanowski (Wojewodzic, 2024, p. 22)

Another prompt structure can be constructed as follows (Wojewodzic, 2024, p. 24):

1. Clear and specific instruction: State precisely what you want the AI to do.

2. Provide an example: Show what the response should look like, and then ask for a similar one.

3. Limit the scope of the response: Indicate how long the answer should be or what it should include.

4. Ask questions step by step: Pose one question at a time and, based on the answer, follow up with the next.

5. Define the response style: Request a specific tone or manner of response (e.g., humorous, formal).

These are simple structures that allow for experimentation with custom prompt versions, making it possible to modify and expand them according to one's needs. The above points provide great flexibility and do not imply that every prompt must contain all elements. One can test different prompting strategies and, over successive cycles, refine and expand the instructions while evaluating the outcomes of such an approach. An interesting prompt structure can also be found below.

The first, known as the declarative instruction scheme, is organized as follows (Wang, Yizhong et al., 2022):

– Definition – a concise and complete definition of the task;

– Positive example – an input presenting a successful outcome, along with a brief justification describing the indicators of desired performance;

– Negative example – an input presenting an unsuccessful outcome, with justification indicating the relevant evaluation criteria;

– Then, provide sample input data and a list of possible valid outputs, which serve to assess the model's performance. This is a standardized, peer-reviewed task description framework from EMNLP, commonly used in research on instruction-tuning. It directly translates into the structure of an effective prompt (definition + positive/negative examples + constraints).

Another approach is ReAct – "Thought → Action → Observation" (Yao, Shunyu et al., 2023):

– Role/Rules (optional: "You have access to tools X. Follow the specified format.")

– Loop format: • Thought: a brief reasoning step • Action: a concrete operation or tool invocation (e.g., "Include […]") • Observation: what the tool/environment returned • Final Answer: concise concluding response/environment returned • Final Answer: concise concluding response

6.5. Support from GenAI Developers

In the process of working with prompts and subsequent iterations of generative models, the companies developing these tools do not leave users entirely on their own. Table 6.4 presents selected guidelines prepared by Anthropic, Google, Microsoft, and OpenAI. In addition, there are optimization tools designed to assist users in formulating valuable and logically coherent prompts.

Table 6.4. Support from GenAI Developers in Prompt Creation

Anthropic	**Microsoft OpenAI**	**Google OpenAI**	**Open AI Open AI**

Clear, direct instructions supported by examples. Use step-by-step reasoning (chain-of-thought). Structure the prompt using tags (e.g. XML). Assign a role (persona), provide a prefilled partial answer, and allow the model to acknowledge uncertainty.	Write in natural language using full sentences. Assign a role (persona) so the model adopts an appropriate perspective. Provide context and clearly specify the expected response format. Be concise and precise, then iteratively refine the prompt.	Begin with a clear objective you want to achieve. Add context to steer the model. Specify expectations for the form and content of the answer. When needed, indicate sources or additional constraints.	Clear and precise instruction: explicitly state what the model should do. Context: include supporting information that helps the model understand the task. Style: indicate tone (e.g. formal, friendly). Iteration: treat prompting as an iterative process test and refine.
Addresses of Guides			
https://docs.anthropic.com/en/docs/build-with-claude/prompt-engineering/overview	https://services.google.com/fh/files/misc/gemini-for-google-workspace-prompting-guide-101.pdf	https://support.microsoft.com/en-us/topic/learn-about-copilot-prompts-f6c3b467-f07c-4db1-ae54-ffac96184dd5	https://help.openai.com/en/articles/10032626-prompt-engineering-best-practices-for-chatgpt
Prompt Optimization Tools			
https://docs.anthropic.com/en/docs/build-with-claude/prompt-engineering/prompt-improver	https://cloud.google.com/blog/products/ai-machine-learning/announcing-vertex-ai-prompt-optimizer	Brak	https://platform.openai.com/chat/edit?models=gpt-5&optimize=true

Source: author's own elaboration based on guidelines from Anthropic, Google, Microsoft, and OpenAI

6.6. Building Prompts in Academic Work and Reducing Hallucinations

For a doctoral student, a prompt is not merely a "question to the chat" but rather a specification of a research task. It should clearly define what is to be done, on what data, in what format, and according to which quality criteria. In most academic applications, a four-element structure is sufficient: a description of the input data, a precisely formulated task, a clearly defined output format, and a brief verification procedure.

When the task is more complex (for example, consolidating multiple articles or drafting a dissertation chapter), it is advisable to include context and constraints such as length, style, prohibitions (e.g., “no citations”), and the quality metrics by which the result will be evaluated (completeness, coherence, precision). A good practice is to provide one short example of the expected output, which helps maintain the desired format in subsequent iterations.

The key principle is this: a prompt should relieve the model of the need to infer anything essential. If you are submitting a full article, specify which elements are priorities (e.g., research question, sample, methods, main results), what the order of sections should be, and whether it is acceptable to supplement the content with general knowledge. Verification should be included directly in the prompt by requesting a list of omissions or uncertainties if some information is missing from the source. Such a safeguard significantly reduces the risk of potential hallucinations.

Example 1. Minimal Template for Summarizing a Chapter

```
## Input data: full chapter text (provided below between markers).

## Task: summarize the content in 150–180 words for an academic reader.

## Output format: single paragraph, formal language, no citations.

## Verification: at the end, add 1–2 sentences "Gaps/uncertainties" if any information was missing from the source text.

<< {paste_text_here} >>
```

Source: author’s own elaboration

In addition to simple summaries, it is also possible to formulate an advanced prompt for generating abstracts the shortest but most important genre of academic writing. For a doctoral student, it is crucial to maintain control over structure, length, and tone so that the abstract remains both complete and concise. Below is a ready-to-use prompt for generating abstracts based on an article’s content.

Example 2. Template for Generating Abstracts

```
##Taks objective
Based on the provided information, generate a scientific abstract consistent with the structure of academic publications. Use a formal style without personal pronouns.
##Input data
```

<< { paste_article_text_or_attached_file_name} >>

##Content structure (substance)

Include in order::

1. Objective: the research gap and how it is addressed.
2. Design/Methodology: type of study; data sources (e.g., Scopus, WoS); tools (e.g., AI); standards (e.g., PRISMA).
3. Findings/Conclusions: key results and their significance, written in the active voice.
4. Limitations: methodological and substantive, described objectively.
5. Practical implications: who can use the results and how.
6. Originality/Value: what new contribution the work makes.

##Output format

- One cohesive paragraph, 250–300 words long (no bullet points or headings).
- Precise, factual language; no citations or bibliographic references.

##Verification

If essential information is missing from the data, add one line after the paragraph: “Gaps/uncertainties: …” (maximum three items).

##Result

[Insert only the abstract (and, if applicable, the “Gaps/uncertainties” line). Do not copy the headings from the prompt.]

Source: author’s own elaboration

Language models tend to mix output with fragments of the instruction, especially when prompts are written loosely within the text. The use of double hash marks (##) acts as segmentation signals, clearly marking the sections of the command (objective, input, rules, format, output). This structure has three practical advantages.First, it helps maintain order in long prompts, making it easy to add or remove sections without disrupting the rest. Second, it reduces the risk that the model will insert technical phrases into the answer (such as "use the active voice"), since they are separated from the "Result" section. Third, it promotes reproducibility: when prompts are stored in a repository, a consistent order of sections facilitates versioning and A/B testing.

To make this separation effective, four rules should be followed. First, maintain a consistent order: Objective → Input Data → Rules/Structure → Format → Verification → Result. Second, use clear data delimiters (<<…>>) so the model can distinguish between the source content and the instruction. Third, prohibit copying section headers into the response this should be stated explicitly in the "Result" section. Fourth, include a safety mechanism: request a bulleted list of missing information whenever the data are incomplete. In practice, this final line most effectively reduces the risk of hallucinations.

6.7. Dividing Work into Stages in Prompts

In academic practice, the best prompts do not delegate the entire task to the model at once. Instead, they break the task down into clear stages and guide the model through successive milestones from fact extraction, through synthesis and outlining, to verification. This structure increases accuracy, facilitates quality control, and allows the user to pause after each step to refine or adjust details. Below is a concise description of the staging method, the rules for using headers (##) in command structures, and complete ready-to-use examples, including a full pipeline for creating a scientific abstract.

Staging solves three common problems: model overload, lack of reproducibility, and token or output limits as well as hallucinations. When the model receives small, well-defined steps (for example, "first extract methods, then generate the abstract"), the risk of speculation decreases and the output becomes easier to verify. In addition, after each stage the user can decide whether to "continue," "revise," or "change criteria." For a doctoral student, this translates into significant time savings while maintaining substantive control.

Instructions should be divided into blocks marked with the header symbol (##). This notation clearly separates the goal, input, steps, output format, and verification, with room for additional clarifications in each section. Source data can be enclosed in delimiters <<<…>>>

so that the model does not confuse them with the instructions. In the "Result" blocks, it is advisable to specify that section headers should not be copied into the response and that the process should pause to ask whether to continue.

Example 3. Prompt Dividing Work into Stages

```
##Objective
Briefly state the goal and its rationale (1–2 sentences).

##Input data
<< {paste_text/table_here} >>
```

```
##Stage 1 - Extraction
Instruction: specify what to extract from the input and in what format (for example,
CSV file or table)
Output: [describe the format here].
After completion, ask: „Proceed to Stage 2? [Y/N]". Stop.

##Stage 2 – Synthesis/Outline
Instruction: organize a content outline or map based on the elements from Stage ..
Output: [e.g. bulleted list].
Ask for confirmation to proceed to Stage 3. Stop.

##Stage 3 – Draft/Initial Version
Instruction: write the first draft following the outline..
Output: [e.g., 250–300 words, one paragraph].
Ask for confirmation to proceed to Stage 4. Stop.

##Stage 4 – Verification and Revision
Instruction: list gaps/risks (max 3) and generate an improved version.
Output: [final text + "Gaps/uncertainties," if applicable].
```

Source: author's own elaboration

Creating a coherent abstract that meets academic standards requires not only familiarity with the content of the article but also the ability to work step by step. For this reason, the following scheme has been prepared on the basis of the previous structure, but expanded and adapted to include elements specific to abstracts. Dividing the work into stages separates data extraction from synthesis and editing, which minimizes the risk of omissions or hallucinations.

Example 4. Extended Scheme for Working on an Abstract

Objective
Prepare the final abstract in line with academic practice based on the provided study data..

Input data
<< { paste notes or article summary here} >>

##Stage 1 – Field extraction
From the input, extract precisely and without adding information:
- study objective (what gap is addressed and how),
- design/methodology (type of study; data sources, e.g. Scopus/WoS; tools, e.g. AI; standards, e.g. PRISMA),
- key results (most important figures/findings),
- conclusions (significance of the results),
- limitations (methodological and substantive),
- practical implications,
- originality/added value.

Return the result as a JSON object with the keys: objective, methodology, results, conclusions, limitations, implications, originality.

After returning the JSON, write: “Stage 1 completed. Proceed to Stage 2? [Y/N]”. Stop

##Stage 2 – Abstract outline
Based on the JSON, create a 6-point outline in the following order:

1) Objective, 2) Methodology, 3) Results, 4) Conclusions, 5) Limitations, 6) Implications and originality.
Each point max. 20 words. Do not introduce any new information
E End with the question: “Stage 2 completed. Continue to Stage 3? [Y/N]”. Stop.

##Stage 3 – Abstract draft
Write one cohesive paragraph of 250–300 words in a formal style, with no headings and no citations. Follow the order in the outline; use active voice and precise formulations.
End with the question: “Stage 3 completed. Run verification (Stage 4)? [Y/N]”. Stop.

##Stage 4 – Verification and revision
1. List “Gaps/uncertainties” (max. 3) if any information is missing from the input data
2. Edit an improved version (same word limit), correcting stylistic and logical issues.
Return:
- Gaps/uncertainties: …” (or “none”),
- „Abstract – final version: …”

Source: author’s own elaboration

Working on an abstract in four stages (extraction, outline, draft, and verification) allows the text to be built gradually while maintaining control over both its content and form. Dividing the task into smaller steps reduces the risk of errors, and the final verification section serves as a safety mechanism, identifying potential gaps and ensuring overall coherence. In this way, the process becomes not only a tool for accelerating work but also a method for cultivating a systematic and methodical approach to academic writing.

Task to Complete
Task objective: compare the draft and the final version to observe how the verification stage affects the quality and precision of the abstract.
Choose one scientific article (for example, from your doctoral bibliography) and apply the above pipeline in practice:
Stage 1 – Extraction: extract the key information from the article and record it in JSON format.
Stage 2 – Outline: based on JSON, prepare a six point abstract plan (maximum 20 words per point).

Stage 3 – Draft: write a single paragraph (250-300 words) a formal style following the order given in the outline.
Stage 4 – Verification: identify up to three “Gaps/uncertainties,” then revise the draft to create the final version of the abstract.

Source: author’s own elaboration

Summary of Chapter 6

Developing one’s own prompting style tailored to individual needs is a continuous process. These skills can also be cultivated through dialogue with chatbots by requesting guidance and receiving feedback on the structures of the prompts used. Effective solutions and prompts that yield satisfactory results should be stored in a personal library for future reference and further development. The advancement of competences in prompt engineering is directly linked to the growth of a young researcher’s didactic and scientific practice. Experiencing and drawing conclusions from the integration of generative AI form a continuous cycle of reflection and refinement of the methods and tools used within the prompting process.

7. AI in Writing Scientific Publications

Artificial intelligence increasingly supports researchers in the process of writing scientific publications from literature review and language editing to the automation of selected stages of analysis. Generative tools, such as large language models, offer the possibility of faster drafting, organizing text structure, and creating summaries. This chapter presents examples of AI applications in writing and editing academic papers, discusses various strategies for collaboration with these systems, and highlights best practices that ensure the integrity and transparency of publications

7.1. AI Tools Used in Scientific Work

ChatGPT and Other LLM-Based Chatbots

A great deal of information about tools such as ChatGPT, Gemini, Claude, and Copilot can be found throughout this publication. Given their continuous development, this section highlights those functionalities that most effectively support the achievement of high-quality results. The focus here is on ChatGPT, as it currently offers the widest range of features not yet available in the other tools. ChatGPT includes a user menu section that allows for personalization by providing the model with background information about the user. A dedicated form enables users to enter details such as their professional experience and specific preferences regarding how the chat should communicate its tone, level of formality, and overall style. Completing this information allows for deeper calibration of the chat/model to individual needs.

Another important functionality is memory. ChatGPT can remember and store information about the user so that it can access it during future conversations. These saved data can be found under the Personalization → Memory management menu. Within this section, it is also possible to enable or disable the option that allows the model to access information from previous conversations, which it uses to generate more personalized responses. To maintain data control and the quality of outputs, users can also create temporary chats, which are not saved in the conversation history. This feature is useful for discussions where the user prefers not to contribute data to the stored memory set. As these tools evolve rapidly, it is likely that similar or parallel functionalities will appear in other services. Their use is recommended, as they improve personalization and calibration, leading to better, more relevant results in both academic and research contexts.

NotebookLM

NotebookLM is one of Google's tools powered by the Gemini model. It differs from typical generative AI solutions in that it allows users to work exclusively with their own data sources and limits its responses to the materials provided by the user. In the free version, users can work simultaneously with up to 50 documents, each limited to 500,000 characters.

NotebookLM supports various file formats, including:

- Text files: PDF, .txt, Markdown, Google Docs, Google Slides
- Audio files: MP3, WAV, M4A, MP4, AIFF, AAC, CAF, AMR (audio files are transcribed, and the text is stored as a source)
- Web content: links to websites (only text is imported) and links to public YouTube videos (the transcription is imported)
- Other: copied and pasted text

The responses generated by NotebookLM are not only based on the provided materials but also include interactive citations, highlighting the exact portions of the sources used to generate each answer. This significantly minimizes the risk of hallucinations and gives users greater control over the accuracy of the results.

Additionally, NotebookLM offers features such as the generation of podcasts and videocasts enhanced with infographics. These resources synthesize the uploaded materials, and the generated content can also be produced in Polish. This makes it possible to create outputs that are not only textual but also facilitate learning and knowledge reinforcement through multiple modalities.

Scite.ai - Smart Citations and the AI Assistant in the Work of a Young Researcher

Scite.ai is an AI-powered research platform distinguished by its Smart Citations database. Each citation in this database is classified as supporting, contrasting, or merely mentioning a given finding, allowing the researcher to position a work within the broader context of the entire scientific corpus. The platform combines access to both open-access and subscription-based content with full-text processing, while the Assistant by scite module generates responses with clearly visible source references, thereby reducing the risk of hallucinations typical of language models. The tool is used by individual researchers and institutions (universities, publishers, companies) and has been developed since 2018. Now part of Research Solutions, scite also offers a browser extension, analytical dashboards, bibliography checking, and a citation statement search engine.

The use of scite in literature reviews operates in a conversational mode: the user formulates a query in natural language, and the Assistant provides a concise response accompanied by a list of publications with DOIs and citation contexts. This allows researchers to assess, even at the level of a single paragraph, whether citations support, contradict, or merely mention the claims being discussed. The Citation Statement Search function further enables searches directly by citing sentences extracted from full texts, which facilitates the rapid identification of specific evidence, such as descriptions of methods, results, or limitations. Within the same environment, users can create collections of articles, assign labels, obtain aggregated statistics, and set notifications about new citations and publications in a given field.

Configuring the Assistant's operating parameters plays a crucial role in ensuring the quality of results. Figure 1 presents the Assistant Settings panel, where users can specify the requirement to include references (always recommended), the type of evidence sources (only abstracts, only citation sentences, or both combined), the article sections to be considered as evidence (for example, Methods or Results), table-mode responses, year range, publication types (peer-reviewed articles, reviews, preprints), citation style (for example, APA), generative model, response length, number of publications consulted per answer, and the reference ranking criteria.

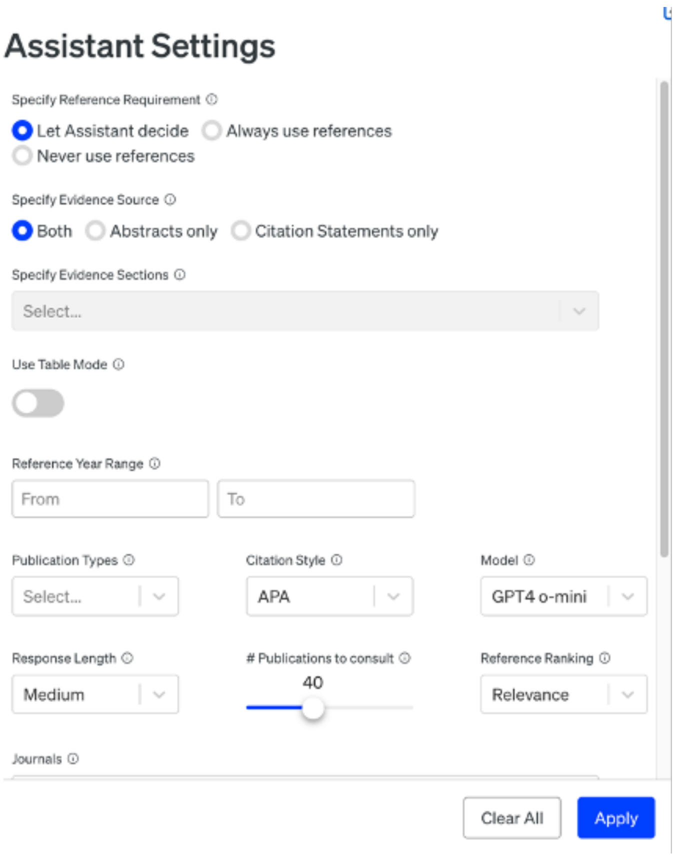

Fig. 7.1. Assistant Settings panel in scite.ai, showing the main configuration switches.
Source: scite.ai

Setting publication year and typology filters, as shown in Figure 7.1, allows for precise control over the currency and credibility of results, while increasing the Publications to consult parameter typically enhances the completeness of synthesis at the cost of longer generation time. An additional Journals field enables limiting the query to selected journals, which is particularly useful when constructing a literature map for narrow research areas.

The Assistant's response takes the form of cohesive paragraphs with embedded references to the literature, which can be treated as a concise overview of the research state. Figure 7.2 illustrates this format: the paragraphs summarize key themes, accompanied by discreet bibliographic links that, when expanded, lead to the full citation context in Smart Citations. A closer examination of several key entries allows users to quickly assess which claims are broadly supported and which remain disputed. Information about the nature of each citation (supporting, contrasting, mentioning) facilitates the prioritization of sources and citation decisions.

In the response settings, it is possible to enable a *tabular mode* for comparing methods, populations, or metrics; however, even in text mode, the Assistant maintains a clear and thematically structured layout.

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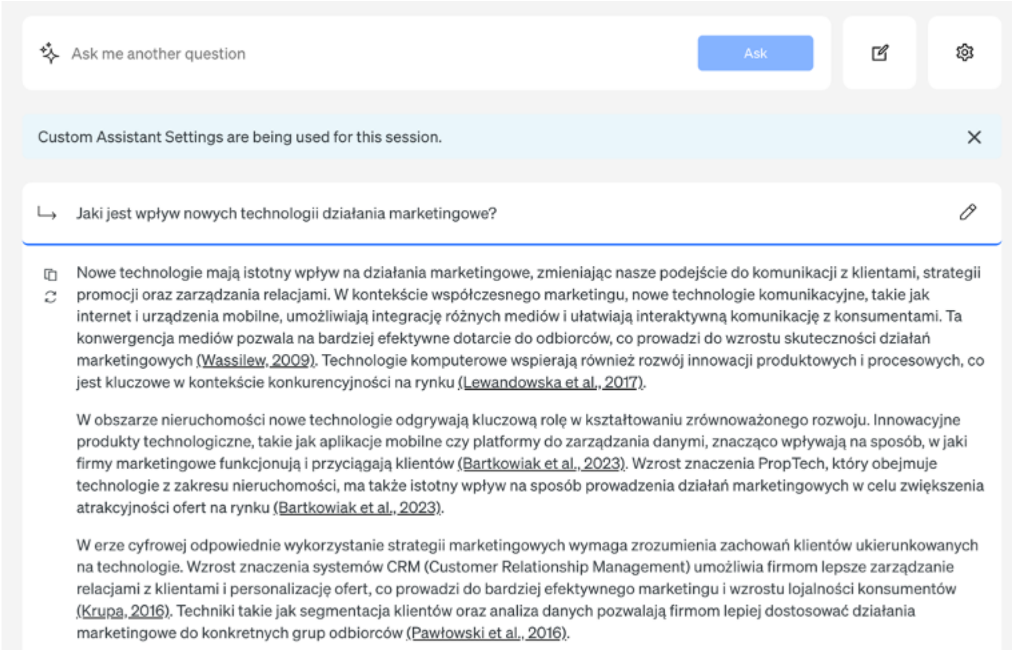

Fig. 7.2. Example of a scite.ai Assistant response to a research question

Source: scite.ai

Source selection transparency is ensured through a dedicated tab containing references and the applied search strategy. Figure 7.3 presents a numbered bibliography with DOI identifiers, along with details of the query procedure used by the Assistant (including search phrases and filters). Such documentation facilitates the replication of the search process in review and methodological studies and also improves communication with supervisors and reviewers.

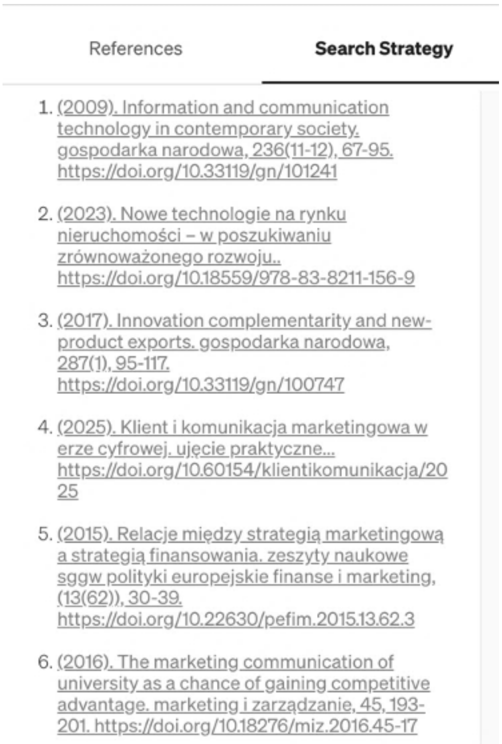

Fig. 7.3. List of Sources and Search Strategy Tab

Source: scite.ai

It is worth noting that scite allows users to upload their own materials in the *Sources* tab. Once added, the Assistant includes these documents in the pool of publications and can cite them explicitly alongside external sources. This feature supports the integration of literature review results with project reports, preprints, or the author's own publications.

From the perspective of a doctoral researcher, the tool supports several common research scenarios. For a quick topic reconnaissance, it is recommended to enable mandatory references and include both abstracts and citing sentences while restricting the publication years to ensure relevance. When preparing a literature scope review, it is useful to narrow the document types to peer-reviewed and review papers and to use the tabular mode, which facilitates comparison. At the manuscript finalization stage, the *Reference Check* function helps assess the quality and recency of citations and quickly identify references to controversial findings. For methodological questions, it is advisable to select the *Methods* section in the settings and restrict evidence to citing sentences only, which increases the precision of references.

Using Smart Citations encourages critical reading but does not exempt researchers from verifying the original context. Each citation should be checked directly in the source text, especially when it is classified as contrasting. In research practice, it is also important to adapt the final bibliography to the requirements of the university or journal, even though scite offers formatting in popular styles such as APA.

The entire infrastructure has been designed with transparency and copyright compliance in mind, which is reflected in its approach to citing full texts and displaying citing sentences rather than reproducing extensive excerpts.

Scite integrates full-text search, citation classification, and a conversational assistant within a single verifiable working environment. This allows researchers to map literature more efficiently, manage bibliographies consciously, and connect review findings with their own materials.

Elicit - assistant for Literature Reviews and Data Extraction

Elicit is a tool designed to support researchers in automating tasks that involve working with large collections of scientific publications. The software accelerates article summarization, data extraction, literature selection, and synthesis of findings. According to the developer, systematic reviews conducted in Elicit can take up to 80% less time, and each response is supported by a direct citation from the original source.

The system searches a database of over 125 million publications and allows users to instantly add up to 500 related articles to their personal collection. A particularly important feature is the transparency of the evidence path: from each generated answer, users can navigate directly to the relevant text segment in the PDF, which facilitates verification and auditing of the process performed by the software.

Work begins with building a private source library. Articles can be added by dragging and dropping PDF, BIB, or RIS files or by selecting them from disk. The import interface is shown in Figure 7.4.

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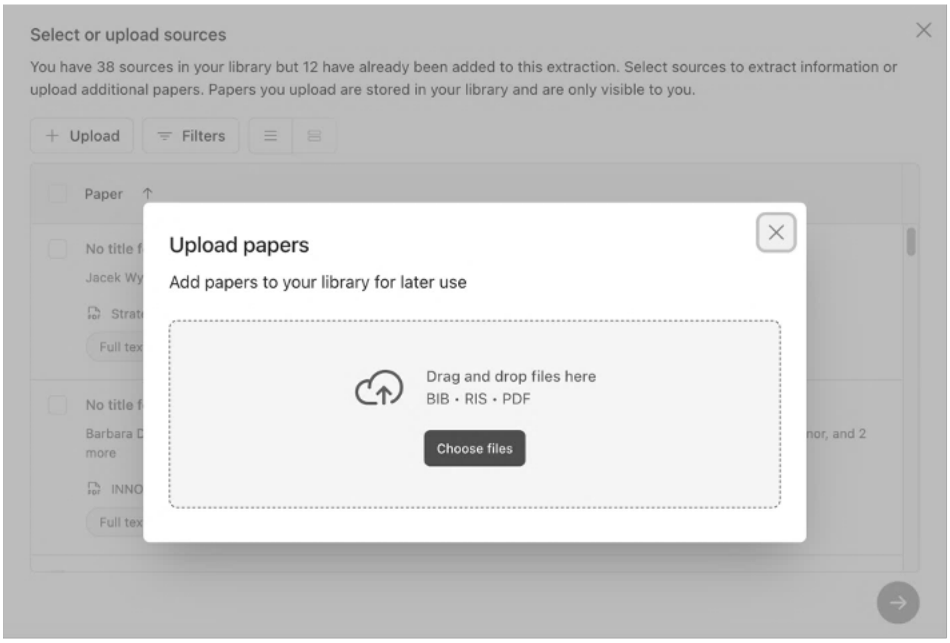

Fig. 7.4. Upload papers – adding PDF/BIB/RIS files to a private Elicit library..
Source: elicit.com

After uploading the materials, the next step is to define which information should be extracted from the papers. This is done through the Manage Columns panel, shown in Figure 7.5, where users can search for existing columns (for example, Limitations, Outcome measured) or create their own.

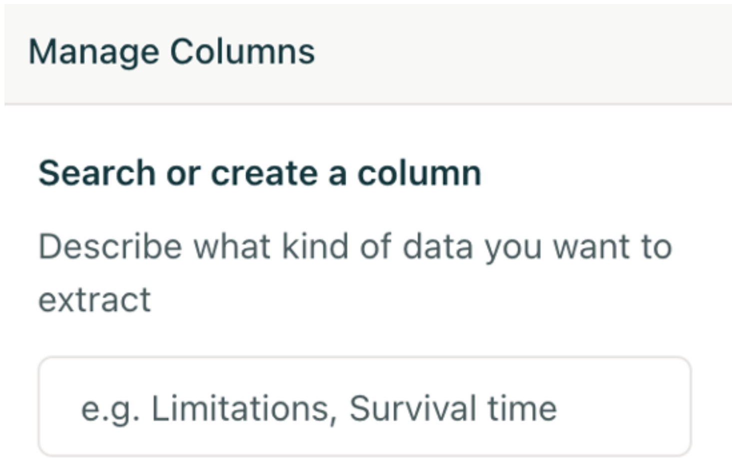

Fig. 7.5. Manage Columns - tworzenie lub wybór kolumn do ekstrakcji danych.
Source: elicit.com

Each column includes an *Instructions* field, a space for a precise prompt describing the extraction method. Figure 7.6 shows the column editing form with an example instruction designed to produce short, single-sentence bullet points summarizing the study results.

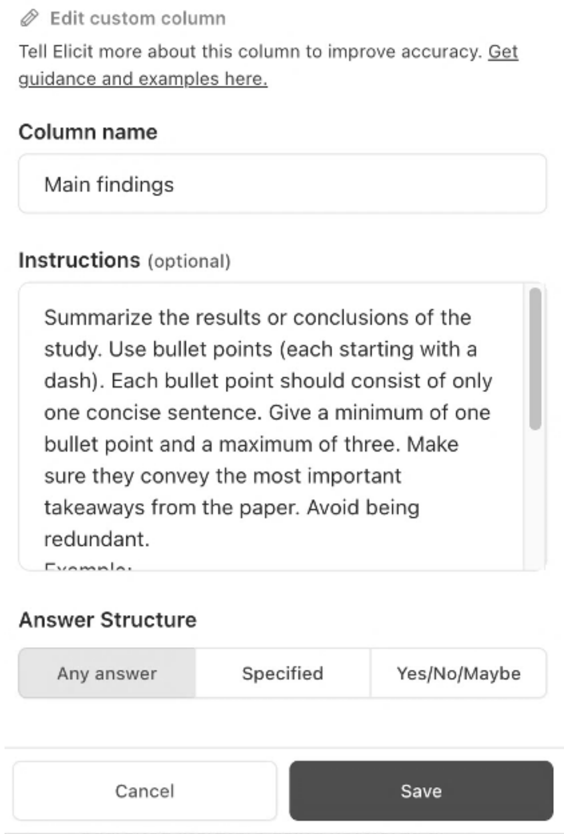

Fig. 7.6. Edit custom column - The *Instructions* field for formulating custom prompts. Source: elicit.com

The practice of prompt iteration is facilitated by the column menu (editing, duplicating, filtering, and saving as a preset), as shown in Figure 7.7.

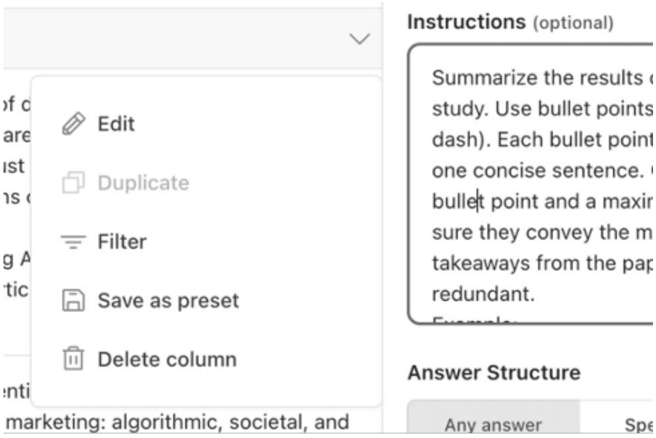

Fig. 7.7 Column menu – editing, duplicating, filtering, saving as preset
Source: elicit.com

The response format can be further standardized using the *Answer Structure* option. Selecting *Any answer* leaves the model flexibility within the given instructions, while *Specified* allows for a strictly defined structure. The *Yes/No/Maybe* option supports binary or multiple-choice coding when assessing the risk of bias. The response structure selection panel is shown in Figure 7.8.

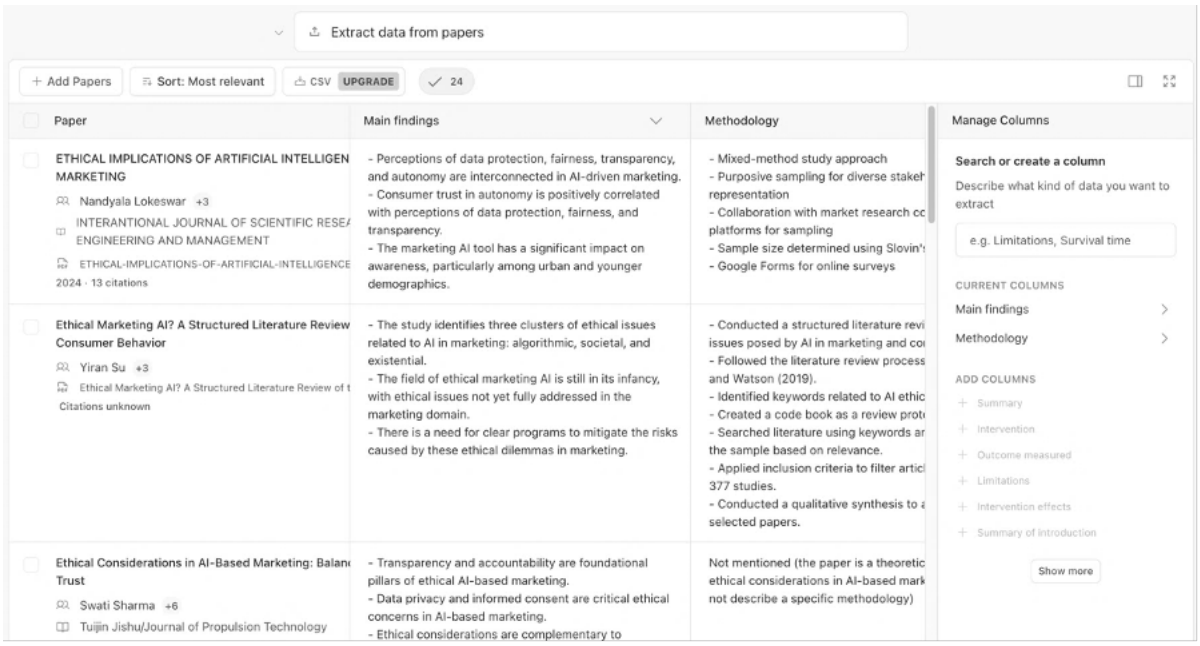

Fig. 7.8. Extraction table – example entries for the columns *Main findings* and *Methodology*
Source: elicit.com

The extraction results are presented in a table where each row corresponds to one publication, and the columns are filled with content tailored to the instructions used. A sample view of such a table, with the columns Main findings and Methodology, is shown in Figure 7.8. This interface provides a convenient environment for further sorting, filtering, and expanding the project with additional columns. In paid plans, exporting to CSV is also available.

Elicit offers a set of functions designed to support evidence-based research. The systematic review module guides users through the stages of searching, screening, extraction, and synthesis. Filtering can be partially automated: the system generates inclusion criteria along with preliminary assessments, which are then subject to verification.

Extraction can scale to hundreds of studies within a short time, including information contained in PDF tables an area that often poses difficulties for manual analysis. The *Elicit Reports* component allows users to create quick, editable reports based on automated reviews, with full transparency and the option to review and revise every step. Working with multiple files simultaneously enables cross-questioning and comparative analysis without leaving the interface.

The effectiveness of Elicit depends on the quality of the instructions defined in the Instructions field. A well-designed prompt should specify the scope (for example, only the *Methods* and *Results* sections), format (for example, short bullet-point sentences or predefined fields), length constraints, and expected measurement units, as well as require the inclusion of a citation supporting each answer. Applying these principles ensures comparable rows across the table and minimizes discrepancies between publications. In practice, it is useful to duplicate effective columns, modify them iteratively, and then save them as presets for future projects. The more knowledge the user has in prompt engineering, the better the results will be. Therefore, proper and professional use of research tools requires a basic understanding of working directly with language models and prompting, as described in Chapter 1 of the practical part of this monograph.

The process of conducting a systematic review in Elicit is organized and methodical. After defining a research question, the researcher imports collected PDF files and extends the database with publications found through the system. Next, filtering is performed using generated criteria, followed by designing a set of columns that correspond to the research question. After the first extraction, it is advisable to check several rows along with their citations and refine the instructions. The next steps include using the *Specified* or *Yes/No/Maybe* options to enforce a consistent format and finally exporting the table for use in a narrative synthesis or meta-analysis. This workflow is transparent and easy to audit, as every piece of information can be traced back to the corresponding source fragment.

Although Elicit significantly reduces the time required for literature-based research, the tool relies on language models which, especially when processing ambiguous PDFs or poor OCR outputs, may still require manual verification. It is essential to consistently check citations and adapt prompts to the specific characteristics of the discipline, including terminology and units of measurement standardization. Better results are achieved by breaking down complex tasks into several simpler columns rather than issuing a single overly general instruction. Following these principles allows researchers to fully leverage the tool's potential while maintaining high-quality, verifiable information reflected in cited sources.

Elicit represents a professional platform supporting literature-based research. The integration of search, filtering, extraction, and reporting within a single environment, along with the ability to precisely control response format through custom prompts and structured output, results in significant time savings while ensuring methodological transparency.

7.2. Different Strategies for Collaboration with AI

Collaboration with artificial intelligence systems can take various forms from creative training and editorial assistance to the automation of selected stages of the research process. A review of different practices shows that the most effective models are those in which humans and machines complement each other's competencies, shifting the researcher's role from performing repetitive tasks toward process management, quality control, and interpretation of results (Tomczyk, Brüggemann & Vrontis, 2024).

The first strategy treats AI as a writing and editorial assistant. Generative tools help organize text structure, suggest argumentation frameworks, and refine style to align with disciplinary conventions. However, the author's role remains central: they define the direction, verify content, and ensure integrity. AI is not the author of the publication and cannot replace human authorship (Haber, Przegalińska & Jemielniak, 2025).

The second strategy involves using AI as a partner in literature review. Comparative studies indicate that traditional databases such as Scopus and Web of Science still outperform in precision and quality of results, whereas AI-based tools more often uncover unique publications overlooked by conventional reviews. In practice, hybrid approaches combining traditional database outputs with AI-generated suggestions prove most effective (Tomczyk, Brüggemann, Mergner & Petrescu, 2024).

The third strategy centers on the automation of review stages, such as article selection, data extraction, or updating findings in dynamic reviews. Literature highlights that such support enhances efficiency and can improve methodological quality provided that the researcher supervises the entire process and remains responsible for the content and conclusions (Tomczyk, Brüggemann & Vrontis, 2024).

The fourth strategy focuses on knowledge mapping. Beyond traditional science mapping, researchers can use approaches that emphasize variables and their relationships, which better support the formulation of research problems and the identification of gaps in the literature. This direction, developed within *variable science mapping*, shows when it is beneficial to combine mapping with other review techniques (Tomczyk, Brüggemann & Paul, 2024).

The fifth strategy emphasizes conscious, transparent, and ethical use of AI tools. Institutional and disciplinary guidelines agree that researchers must clearly disclose the role AI has played, ensure verifiability, and safeguard both research integrity and participant well-being. In practice, this entails documenting tool usage, describing model roles and limitations, and providing information for reviewers and readers (European Commission, 2025; Cheng, Calhoun & Reedy, 2025).

The sixth strategy underscores creative collaboration. Publications and AI-generated book projects demonstrate how AI can become an interactive dialogue partner, inspiring concepts and supporting iterative writing while maintaining full transparency regarding the role of tools and authorial control (Przegalińska & Triantoro, 2024).

Finally, collaboration with AI should be embedded within a broader institutional and team strategy. Treating AI as a permanent component rather than an add-on facilitates competence building, tool selection, and the establishment of quality and disclosure standards. Such an approach strengthens research competitiveness and resilience (Przegalińska & Jemielniak, 2023; Beshr, Ateeq, Ateeq & Alaghbari, 2025).

7.3. Example Workflows for Collaborating with AI

Pathway 1 - Defining rules and responsibility - We begin by selecting tools and writing down the rules for their use: which tasks are supported by AI, how its role will be documented, and how reliability and auditability will be ensured. Current guidelines recommend including a short AI usage statement in the manuscript and in the supplementary materials, together with a description of the stages at which the tools supported the work (European Commission, 2025; Cheng, Calhoun & Reedy, 2025).

Pathway 2 - From research question to study plan - AI can act as a conceptual coach: helping refine the research question, suggest possible operationalizations, and propose design variants. This collaboration is most valuable when it remains a dialogue – the researcher sets the direction, and the tool proposes hypotheses, structural sketches, and examples, which are then critically assessed and revised (Przegalińska & Triantoro, 2024; Haber, Przegalińska & Jemielniak, 2025).

Pathway 3 - Hybrid literature review - First, perform queries in Scopus and Web of Science to build the core of the review. Then ask AI tools to identify missing themes and unique publications. Comparative studies show that this combination increases completeness: traditional databases provide precision and quality, while AI systems increase the likelihood of discovering material outside standard retrieval paths (Tomczyk, Brüggemann, Mergner & Petrescu, 2024a; Tomczyk, Brüggemann, Mergner & Petrescu, 2024b).

Pathway 4 - Mapping concepts and variables - At the synthesis stage, one can use mapping of relationships between variables and theories to move from a list of keywords to a structured view of dependencies in the research field. This supports both the articulation of theoretical contribution and the planning of empirical studies (Tomczyk, Brüggemann & Paul, 2024).

Pathway 5 - Automating selection and extraction - Repetitive tasks such as screening records, extracting metadata, and pulling key information from articles can be automated. It is advisable to maintain dynamic reviews that update as new publications appear. Human oversight remains essential: authors verify relevance and correct model errors (Tomczyk, Brüggemann & Vrontis, 2024).

Pathway 6 - Writing, editing, and quality control - Generative AI can smooth style, shorten passages, and organize argumentative structure, but final wording, factual claims, and interpretations belong to the author. A good standard is to perform an additional citation check and an anti-plagiarism scan, especially when tools summarize external texts (Haber, Przegalińska & Jemielniak, 2025).

Pathway 7 - Disclosure and preparation for review - The manuscript should include a brief statement describing the role of AI. Details should be added in an appendix, and compliance with journal and institutional policies must be ensured. Institutional recommendations stress clarity, reproducibility of the process, and the principle that AI must not be credited as an author (European Commission, 2025; Cheng, Calhoun & Reedy, 2025; Haber, Przegalińska & Jemielniak, 2025).

Pathway 8 – Embedding AI in team and departmental strategy - Teams should agree on shared standards for AI use: approved tools, minimum documentation requirements, and a competence development plan. This strategic approach, familiar from organizational management, increases the coherence and resilience of research processes and supports alignment with academic values (Przegalińska & Jemielniak, 2023; Beshr, Ateeq, Ateeq & Alaghbari, 2025).

7.4. Verification checklists (facts, references, plagiarism)

Reliable verification of content at the end of the research process is the fastest way to avoid a review being rejected for basic errors such as inconsistent claims, incorrect citations, or unintentional reuse of others' wording. A well-structured checklist streamlines this stage by guiding the author step by step through the three most sensitive areas: factual accuracy, references, and textual originality, and only then addressing formal aspects. Below is an introduction to each of these areas and concrete checklists that should be applied before submitting the manuscript.

1. Facts and Consistency of Argumentation

At this stage, the goal is to ensure that all claims are consistent with the data, logic, and evidence that were actually analyzed.

Checklist - Facts and Consistency:

· Does each key claim have clear support in the text in the results, tables, figures, or cited sources?

· Are the numerical values consistent throughout the manuscript (in the abstract, results, tables, sample description, and conclusions)?

· Is statistical significance accompanied by effect size and confidence intervals where appropriate?

· Are the definitions of concepts and variables consistent, without shifting meaning between sections?

· Do the conclusions stay within the limits of what the method and data actually support?
· Are figures and tables numbered, labeled, and referenced in the text, and do captions allow understanding without consulting the main text?
· If AI tools were used for summarizing or drafting sections, has every piece of information been verified against the original sources?

2. References and Citations

A good bibliography is not only about completeness but also about precision: the source must exist, support the argument, and be correctly described.

Checklist - References:

· Is the primary source cited whenever possible (instead of secondary summaries)?

· Do all items in the reference list appear in the text, and vice versa no omissions or duplicates?

· Does each record contain accurate data: authors, year, title, journal name, volume/issue number, pages, DOI, or URL?

· Is the citation style and punctuation consistent with the chosen guidelines (for example, APA) throughout the manuscript?

· Is there no excessive self-citation or overly narrow literature selection, and are works representing different perspectives included?

· Are citations of preprints updated to peer-reviewed versions if they have since been published?

· If AI suggested sources, was each one manually verified (existence, content, relevance to the argument)?
· Do all in-text citations correspond correctly to the entries in the bibliography?

3. Plagiarism, Self-Plagiarism, and Originality of Wording

Originality concerns not only the data but also the way ideas are presented. Therefore, both literal borrowings and excessive paraphrasing should be verified.

Checklist - Originality and Text Ethics:
· Is every direct quotation enclosed in quotation marks, with a page number and full reference?
· Do paraphrases genuinely reformulate others' ideas in the author's own words and include proper attribution (rather than minor lexical substitutions)?
· Have no significant fragments of the author's previously published work been reused without clear indication and justification (self-plagiarism)?

· Have the results not been fragmented into several very similar publications without distinct research questions?
· Has the manuscript been checked with at least one text similarity detection tool, and have the results been reviewed qualitatively (examining the context of matches)?
· If AI assisted in editing, does the final version avoid unmarked, formulaic phrases commonly generated by models and retain the author's individual writing style?

3. Transparency in the Use of AI

If AI tools were used in the process for drafting, organizing the bibliography, paraphrasing, or summarizing it is important to disclose this information.

Checklist – Transparency in AI Use:
· In the *Methodology* or *Statements* section, has it been clearly indicated what AI was used for and how the results were verified?
· Have prompts been checked to ensure that no sensitive data were included, and is the use of AI consistent with the policies of the journal and institution?
· Has it been confirmed that AI models are not treated as co-authors and that full scholarly responsibility rests with the human authors?

5. Final Review Before Manuscript Submission

A brief technical check helps avoid minor issues that often frustrate reviewers.

Checklist - Final Control:
· The title, abstract, and keywords are consistent with the content and terminology of the discipline.
· Supplementary files (data, scripts, preregistrations) are accessible and properly described; all links are functional.
· Declarations regarding author contributions (CRediT), funding, conflicts of interest, and ethical approvals are complete and consistent.
· The manuscript's format, figures, and tables comply with the journal's guidelines; metadata in the reference manager are synchronized with the text.
· All co-authors have reviewed the submission version and approved its content.

Summary of chapter 7

AI can significantly facilitate the process of writing academic publications by increasing work efficiency and supporting the researcher's creativity. At the same time, its use requires critical verification of results to avoid risks related to hallucinations, incorrect citations, or a loss of argumentative coherence. It remains essential to disclose the role of AI transparently, to maintain full authorial responsibility, and to treat models not as substitutes but as supportive tools. In this way, artificial intelligence can become a valuable component of the publication workflow, enhancing the research process without compromising the principles of academic integrity.

8. Automation in research work

Automation is one of the key areas of application for artificial intelligence in scientific work. Thanks to no-code tools and the integration of language models with popular environments such as spreadsheets and bibliography managers, researchers can significantly streamline repetitive and time-consuming tasks. This chapter presents examples of practical solutions that allow you to move from manual analysis to automated workflows, ensuring greater efficiency and better control over your data.

8.1. The concept of "Sheets → AI → report"

This chapter presents a method for building a repeatable text processing workflow in a spreadsheet without writing any code. The foundation of the approach is Google Sheets combined with an add-on that integrates a language model, such as GPT for Sheets™ and Docs, which provides functions that can be called directly within spreadsheet cells. Such an add-on enables AI models to generate responses based on data stored in the sheet and is available through the Google Workspace Marketplace.

The spreadsheet serves as a control panel. Each row represents a publication or another source record. The columns store raw data for example, abstracts while adjacent columns contain the add-on formulas that prompt the model to produce precisely defined results: classification labels, extracted fields (e.g., method, sample), or concise summaries.

Preparing the environment

Installation: The AI integration add-on must be installed from the Google Workspace Marketplace and granted permission to operate within selected spreadsheets.

API Key: The add-on requires an API key obtained from the model provider's platform, such as OpenAI. API keys are created and managed in the OpenAI dashboard (under the API keys section of an account or project). The key is used for authentication of API calls and must remain confidential. It is recommended to store it only within the add-on's settings or in a secure vault, and never expose it directly within the spreadsheet.

Good practices for APIs
- Treat the key as confidential; do not place it in spreadsheet cells or shared materials.
- It is advisable to create separate keys for projects and rotate them periodically.
- Where possible, limit permissions and monitor usage.

Spreadsheet Design

To begin working with the GPT for Sheets™ and Docs add-on, the spreadsheet should be designed to allow for systematic storage of both input data and AI-generated results. The structure should remain simple yet flexible enough to accommodate various types of research information.

A recommended structure includes:

- **ID** - record identifier,
- **Title**, **Year**, **Source**,
- **Abstract** – main text field,
- **Result columns:** Classification, Method, Sample, Context, Main Finding, Summary,
- **Meta columns:** Run Date, Model, Prompt Version.

Task: Create a spreadsheet with the columns listed and enter 3 sample records (abstracts). Then add empty columns for AI results and metadata.

8.2. Binary classification of abstracts

The next step is to perform binary classification of abstracts based on a given criterion. With a properly prepared prompt, it is possible to quickly obtain repeatable results in the form of simple answers.

```
=GPT("Does the abstract address the issue of using blockchain technology to
build customer loyalty? Mark accordingly: yes, no, or 'I am unable to
determine'. If you are unsure, mark 'I am unable to determine'."; L2)
```

Tip. For stable results, it is recommended to set the creativity as low as possible (temperature as shown in Figure 8.1) in order to obtain repeatable results.

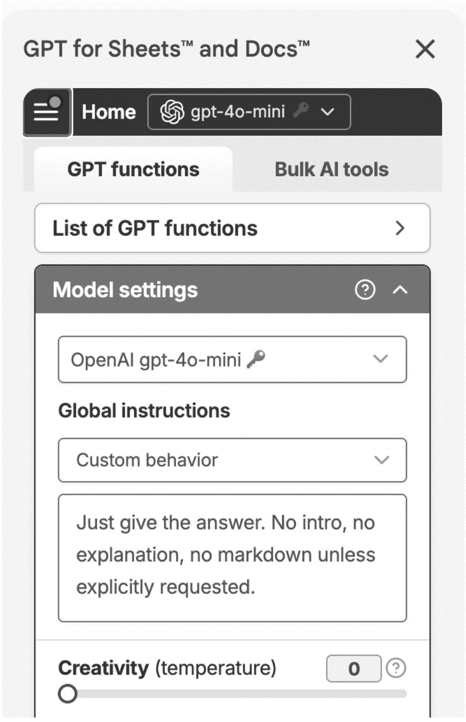

Fig. 8.1. Panel GPT for Sheets™ and Docs z ustawieniami parametru temperatura
Source: own work

Prompt - classification template

Role: reviewer. Task: assess whether the criterion [definition here] is met.

Format: only yes, no, I am unable to determine.

Material: L2.

Task: Classify all 3 abstracts and manually evaluate whether they have been classified correctly.

8.3. Information extraction

In research, it is often important to extract key elements from abstracts, such as the method, sample, context, or main result. Automating this process in a spreadsheet can significantly speed up the analysis of large collections of publications.

```
=GPT("From the abstract below, extract and list in ONE line four pieces of
information in the following order: methods; sample; context; main result.
If information is missing, enter ‘none’. Abstract: " ; L2)
```

Figure 8.2 shows an example set of abstracts with the formula introduced under the GPT for Sheets™ and Docs add-on, illustrating how the model can automatically fill in the columns of the spreadsheet.

fx =GPT("Z poniższego abstraktu wyodrębnij i zwróć w JEDNYM wierszu cztery informacje w kolejności: metody; próba; kontekst;

A	B	C	D	E	F
1	The impact of AI on customer experience Artificial intel	brak; brak; marketing; poprawa doświadczenia klienta			
2	Applications of Artificial Intelligence (AI) in Marketing M	brak; brak; marketing; przegląd podstawowy AI w zarządzaniu marketingiem			
3	How Artificial Intelligence Is Impacting Marketing? Artif	brak; brak; marketing; AI wpływa na działania, umiejętności i wydajność menedżerów marketingu.			
5	The impact of artificial intelligence on improving efficie	analiza literatury; brak; usługi; poprawa efektywności i zadowolenia klientów			

Fig. 8.2. Sample set of abstracts with the formula introduced under the GPT for Sheets™ and Docs add-on

Source: own work

Task: Extract all sample records and manually assess whether the information has been added contrary to the abstract. If necessary, tighten the wording in the prompt (for example, “do not fill in the gaps”).

8.4. Draft abstract

In addition to classification and information extraction, it is also possible to automatically generate short summaries. This feature is particularly useful in comparative analyses or when preparing literature reviews.

```
=GPT("Summarize in 2 sentences (max. 60 words), scientific style, without
recommendations and without sources. Keep the language of the original. Abstract: " ; L2)
```

When not to summarize? In analyses sensitive to the style of the original (e.g., discourse studies), summaries should be used for orientation purposes only, and not as material for coding.

8.5. Validation and replicability

It is recommended to prepare a short codebook of categories. Then, it is worth performing calibration on a random sample (for example, 20-30 manually evaluated records) and only then applying the formulas on a large scale. For replicability, it is a good idea to record the following alongside the results: model name, prompt version, date/timestamp, and parameters (e.g., temperature). The version history of the spreadsheet facilitates auditing changes.

Prompt - calibration (few-shot)
“Here are three examples of classification (abstract → label). Based on these, evaluate the new case. Answer only yes, no, or I cannot determine. New abstract:”; L2

8.6. Privacy and compliance

Sensitive data or information subject to ethical or legal obligations should not be included in the formulas. In the case of empirical material (surveys, interviews), anonymization is recommended. Transparency is recommended in the final documents: marking the sections where AI tools were used and describing the validation method.

8.7. Common problems and solutions

Various technical difficulties may arise when working with the add-in. It is worth knowing the typical sources of errors and how to solve them so that working with the spreadsheet runs more smoothly.

#ERROR! or interrupted operation - possible exceeding of the add-in limits; turning on the RUN switch and running calculations in batches usually stabilizes the operation.

Argument separator - in the Polish localization, semicolons ; are used.

Variability of results - lower creativity (temperature ~0) and more precise formatting are recommended.

8.8. Exercise: mini literature review

At the end of this chapter, a practical exercise is proposed. It allows you to practice all the previously discussed functionalities and independently assess potential limitations and sources of errors.

> Prepare 30 abstracts on a selected topic and enter them into the spreadsheet. Then: (1) perform binary classification according to your own criteria; (2) extract four pieces of information; (3) generate shorter summaries. Finally, it is advisable to add two sentences about the limitations of the procedure and potential sources of error.

Summary of Chapter 3

The examples discussed in this chapter show that automation using AI does not require advanced programming skills and can significantly reduce the researcher's workload in terms of data organization and analysis. Automation does not replace critical thinking or interpretation, but allows you to focus on the creative and conceptual aspects that determine the scientific value of your research.

The AI add-on for Google Sheets transforms the spreadsheet into a text lab for classification, extraction, and summarization. The key is precise prompts with a forced format, simple safeguards (IF, RUN), systematic validation, and documentation of operating parameters. The API key should be obtained from a trusted provider (such as OpenAI) and stored in accordance with good security practices.

9. Detection of AI-generated content

The development of generative artificial intelligence tools has made the distinction between human-created content and text generated by language models a significant challenge for science and education. In response, AI detection systems have been developed that analyze language properties, writing style, and statistical token patterns to determine the likelihood that a given text was generated automatically. This chapter discusses the most important detection tools, their limitations, and the consequences of their use in academic practice.

9.1. AI detectors

Most tools designed to detect text generated by large language models (LLMs) rely on statistical properties of language: perplexity (the predictability of subsequent tokens), burstiness (the variability of token distribution), stylometry, and the log-probability of a sequence computed by a reference model. Classical approaches show that machine-generated texts tend to cluster in regions of lower entropy and higher predictability, which can be visualized or classified (Gehrmann, Strobelt, Rush, 2019; Mitchell, Lee, Khazatsky, Manning, Finn, 2023).

An alternative class of methods is watermarking deliberate, human-imperceptible marking introduced during generation, which later facilitates identifying the origin of the output. In commercial practice, tools combine these signals into classification models and report results as a probability or proportion of AI involvement in a text (Kirchenbauer, Geiping, Wen, Katz, Miers, Goldstein, 2023).

The tool ZeroGPT provides AI/Human classification and a percentage score, purportedly based on measures such as perplexity/burstiness as well as machine-learning models (zerogpt.com). In academic literature, the tool appears in comparative surveys, where it can be competitive for older models such as GPT-3.5, but its effectiveness decreases for newer models or modified texts (Walters, 2023). In Figure 9.1, for a sample of text generated by the GPT-5 Pro model, the tool assessed “AI GPT” at 58.39%, indicating an inconclusive result.

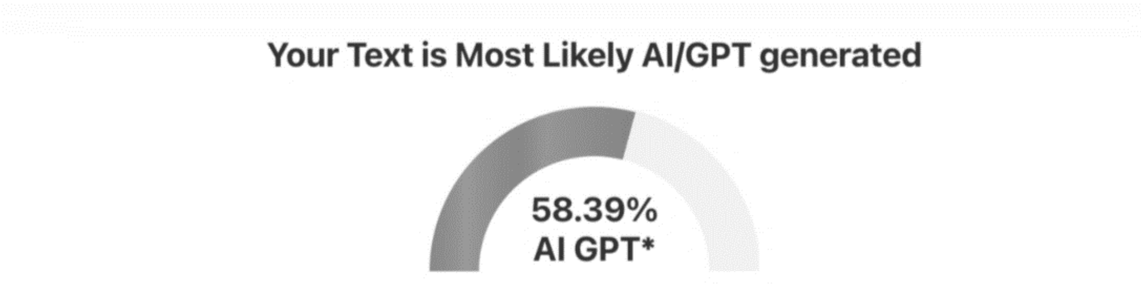

Fig. 9.1. ZeroGPT result for text generated by the GPT-5 Pro model
Source: own research using the tool zerogpt.com

In contrast, in Figure 9.2, the analogous sample of text generated by the GPT-4o model has been marked as 100% AI/GPT.

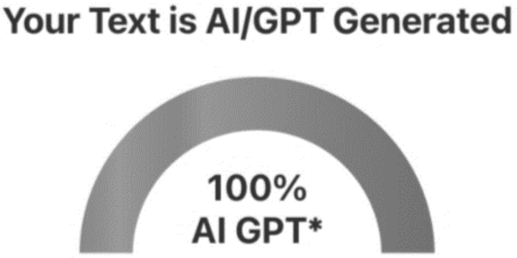

Fig. 9.2. ZeroGPT score for text generated by the GPT-4o model

Source: own research using the tool zerogpt.com

Originality.ai combines AI detection with plagiarism and sentence-level reporting (Originality.ai). In an independent comparative study of 16 detectors (126 essays: GPT-3.5, GPT-4, and student papers) Originality.ai, alongside Copyleaks and Turnitin, achieved high accuracy for all three sets, while many other tools had problems, especially with GPT-4 texts (Walters, 2023). Figure 9.3 and Figure 9.4 show the results of 100% Likely AI for both samples of text generated by the GPT-5 Pro and GPT-4o models, illustrating the strong classification of this detector in the overview tests.

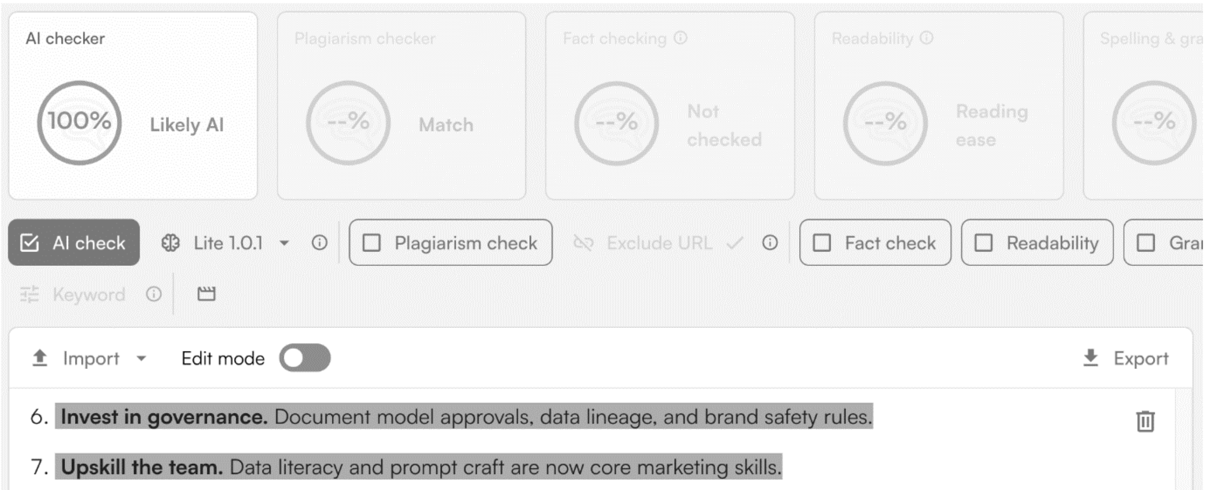

Fig. 9.3. Originality.ai result for text generated by the GPT-5 Pro model

Source: own research using the tool Originality.ai

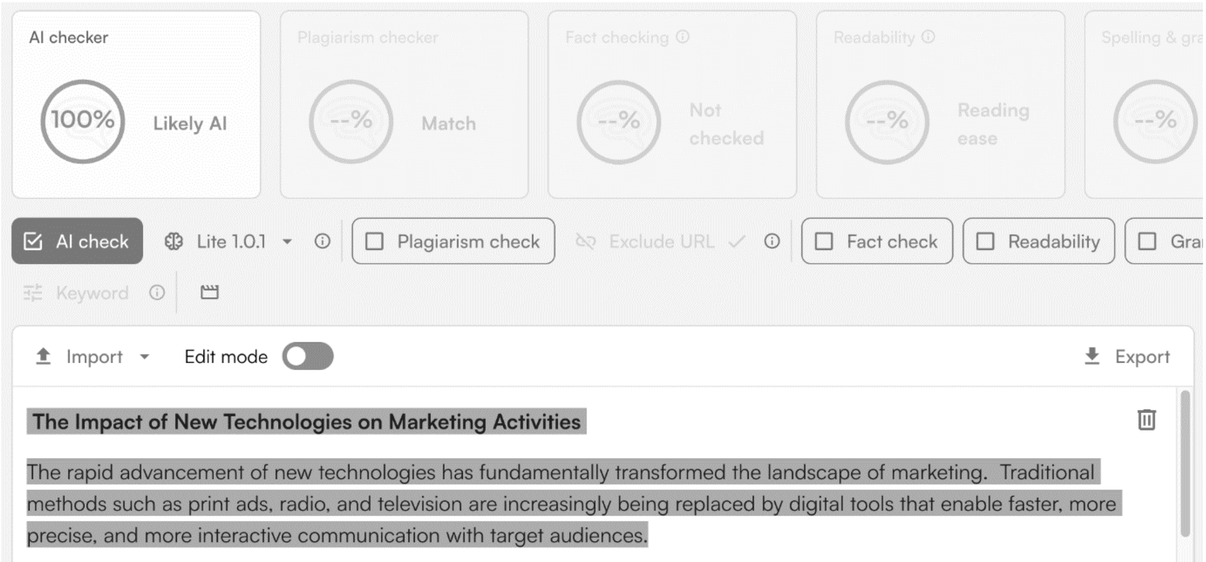

Fig. 9.4. Originality.ai result for text generated by the GPT-4o model

Source: own research using the tool Originality.ai

QuillBot, originally known for paraphrasing, also offers an AI detector that reports the proportion of likely AI text (quillbot.com). Publicly available descriptions of its operation refer to the analysis of linguistic features and comparison of patterns with training data. In scientific literature, the tool is evaluated less frequently, and reports on its effectiveness are mixed. In Figure 9.5, the detector indicated 58% likely AI, which is a partial result, while in Figure 9.6, it identified 100% likely AI.

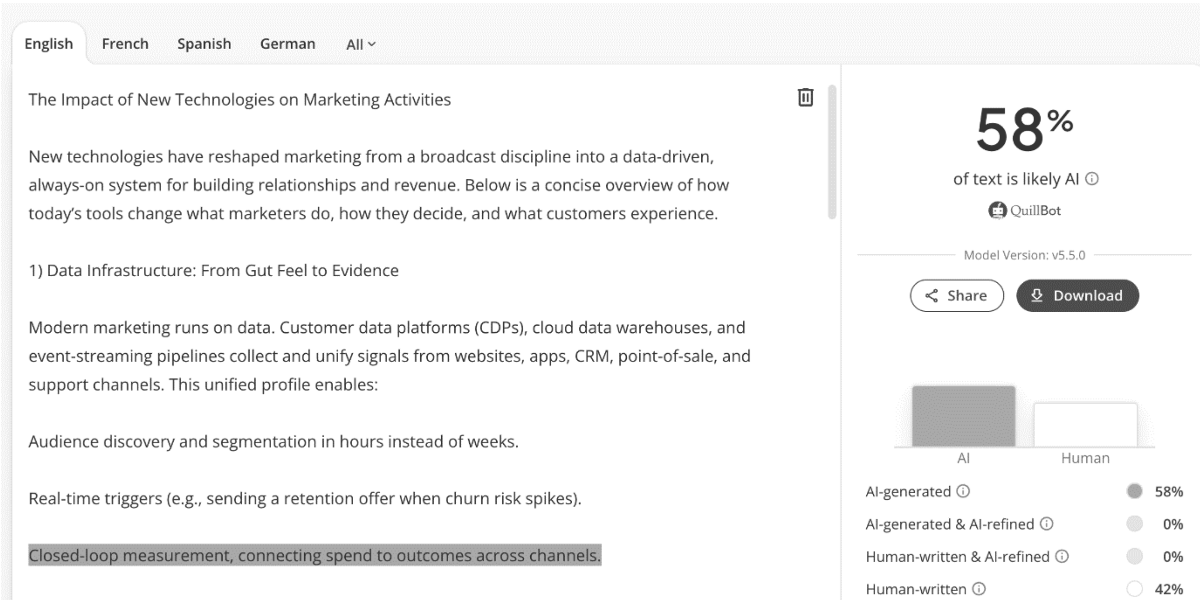

Fig. 9.5. QuillBot AI Detector result for text generated by the GPT-5 Pro model

Source: own research using the tool quillbot.com

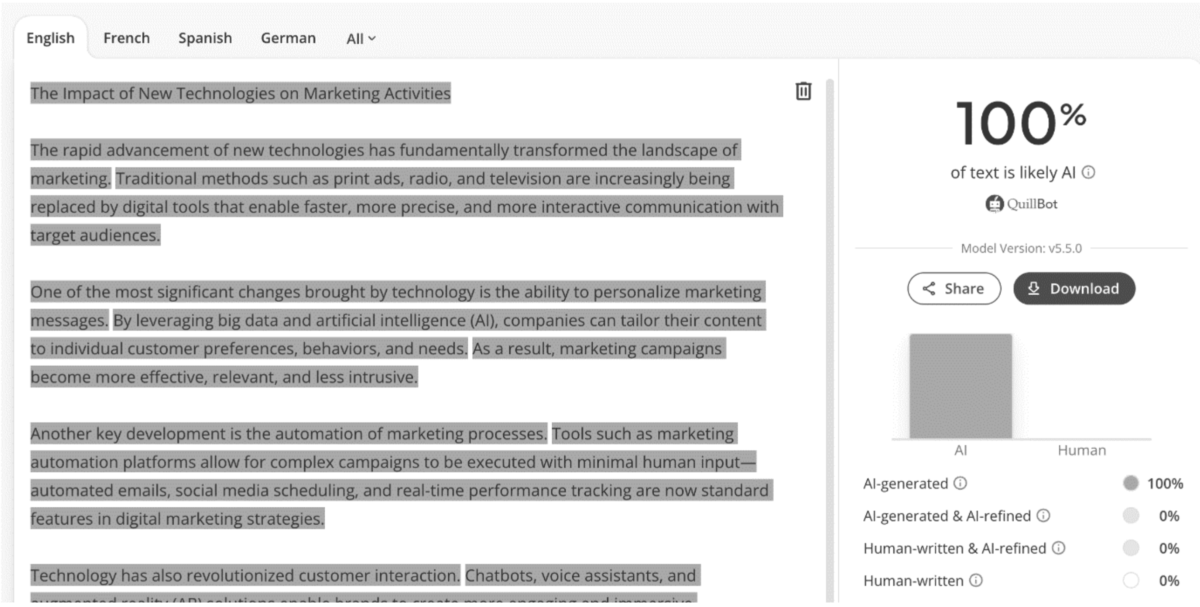

Fig. 9.6. QuillBot AI Detector result for text generated by the GPT-4o model

Source: own research using the tool quillbot.com

Two frequently cited research approaches are GLTR, i.e., visualization of word positions in probability distributions for top-k/nucleus indicators, and DetectGPT the use of conditional probability curvature for zero-shot detection. Watermarking (Kirchenbauer et al., 2023), on the other hand, does not analyze the style of the text, but detects a signal embedded during generation. However, this requires the cooperation of the model creator and is sometimes susceptible to paraphrasing (Gehrmann et al., 2019; Mitchell et al., 2023; Kirchenbauer et al., 2023).

9.2. False alarms and detection limits

Detectors generalize poorly outside their training distributions (e.g., across domains, genres, or registers). OpenAI explicitly stated that its own (now discontinued) classifier had low accuracy, performed poorly on short texts below 1,000 characters, and was less reliable in non-English languages; therefore, it should not be used as a primary decision-making tool. This warning remains relevant for most current detectors (OpenAI, 2023).

A number of studies have shown that even slight paraphrasing whether automatic or manual dramatically reduces detection accuracy (including for DetectGPT, GPTZero, and watermark-based classifiers). Recursive paraphrasing methods can reduce the area under the ROC curve (AUC) by orders of magnitude, with only minimal loss in linguistic quality (Krishna, Song, Karpinska, Wieting, Iyyer, 2023; Sadasivan, Kumar, Balasubramanian, Wang, Feizi, 2023).

In the study by Liang et al. (2023), detectors systematically misclassified texts written by non-native English speakers as AI-generated more often than those written by native speakers. This indicates a real risk of penalizing writing styles that deviate from the training data (Liang, Yuksekgonul, Mao, Wu, Zou, 2023).

An evaluation of 16 detection tools found that while some detectors could distinguish GPT-3.5 output from human text, they were largely ineffective against GPT-4. The best-performing tools Copyleaks, Turnitin, and Originality.ai maintained relatively high accuracy across both datasets. Effectiveness, however, remains sensitive to model versions and constantly evolves (Walters, 2023).

A reported "X% AI" score is heuristic, dependent on sample length and the decision threshold used. The same text can be classified anywhere from 'unclear' to '100% AI' by different detectors (see Figures 1–6 for the same pair of text samples generated by GPT-5 Pro and GPT-4o). Users should treat such indicators as guidance rather than evidence (OpenAI, 2023).

Peer-reviewed research provides the strongest empirical support for Originality.ai, which consistently achieved high results across 16-tool comparisons, including GPT-4 datasets. ZeroGPT can be effective but shows high variability in independent tests, especially with newer models and edited texts. QuillBot AI Detector has the weakest coverage in the scientific literature mostly marketing descriptions and journalistic reviews so its results should be interpreted with particular caution (Walters, 2023).

If a detector is to be used at all in educational or editorial settings, it should serve only as a supporting tool, ideally in combination with at least two different detectors, and accompanied by verification of the text creation process (e.g., version history, notes, drafts, citation logic).

Recommendations for early-career researchers and PhD students:

- Do not base decisions solely on a detector. Even developers and researchers emphasize limited reliability and high false-positive risk for short or paraphrased texts. Preserve process evidence such as drafts, notes, and code repositories (OpenAI, 2023).
- Cross-check results from multiple sources. Combine at least two detectors with substantive evaluationmethodological coherence, citation accuracy, and plagiarism control.
- Be aware of bias (AI bias). For non-native authors or works with unconventional terminology, consider the possibility of model bias (Liang, 2023).

- Understand technical limitations. Statistical detection ≠ authorship determination; watermarking requires generator-side support and can also be bypassed through paraphrasing (Kirchenbauer, 2023).

Chapter 9 Summary

AI detectors are useful as risk indicators, but they do not provide proof of authorship. The sample tests presented (Figures 1-6) reveal notable discrepancies between tools, especially for text generated by GPT-5 Pro, and the academic literature confirms that paraphrasing, editing, and author population differences significantly increase false result rates.

Among the three tools discussed, Originality.ai has the strongest empirical validation in comparative studies; nevertheless, every result must be interpreted cautiously and supplemented with an assessment of the text creation process (Sadasivan, 2023; Walters, 2023).

10. Creating and Updating Educational Materials

Generative artificial intelligence can also serve as a tool for supporting the preparation of educational materials. Its key features that make this possible include speed, the ability to analyze and synthesize vast amounts of data, and adaptability to user needs. A new and particularly significant element in the educational context is multimodality (Smith et al., 2025).

This refers to the ability to use and generate textual, auditory, and visual resources. In teaching practice, it enables educators to present content through multiple forms of representation, reaching students through the channel that is most accessible to them at a given moment. Research on digital multimodal composition predominantly highlights its potential to enhance student engagement, affirm identity, and support innovative meaning-making (Smith et al., 2025). The multimodal nature of GenAI enhances didactic agency by allowing the creation and analysis of content in formats more closely aligned with academic practice (text–image–audio–video), as well as by supporting reflection on teaching based on video data (Imran et al., 2024).

With current GenAI tools, it is easy to navigate and transform materials across multiple modalities text to audio, audio to text, visualizations, simulations, and even platforms and tools supporting AR and VR (Hemminki-Reijonen et al., 2025; Lampropoulos, 2025).

As in every aspect of a young researcher's work intended to create value, teaching activities also require a clearly defined purpose for using a given tool or resource. Despite the ease of generating presentations, worksheets, case studies, or other technologically advanced materials, the essential task remains integrating these elements into the process of designing or expanding students' learning environments. This approach aligns with the ARCHED framework (Responsible, Collaborative, Human-centered Education Instructional Design) (Li et al., 2025), which emphasizes the need to define precise educational goals consistent with Bloom's taxonomy at the design stage of AI-assisted materials, while maintaining the central role of the teacher as the primary decision-maker in the instructional process.

10.1. Creating Syllabi and Case Studies

Preparing syllabi or case studies for academic teaching is often a time-consuming process that requires considerable effort. However, with access to a repository of previously developed syllabi or case studies, along with institutional guidelines specifying their required components, this process can now be streamlined through the use of generative artificial intelligence.

The key factor here is working with verified and well-structured data, previous syllabi, case studies, and institutional templates which serve as the foundation for quality and coherence. Based on these materials, AI can suggest modifications to existing documents, generate preliminary drafts, or create new content for specific sections (e.g., learning outcomes, assessment methods, reading lists). As with other areas of academic work, the process follows an iterative cycle, allowing users to progressively refine individual sections and decide at which stage to conclude collaboration with the chatbot.

An example of a prompt (which can be modified according to specific needs) might look as follow:

You have received a collection of documents containing previously developed syllabi and institutional guidelines for academic courses. Based on these materials, prepare a new syllabus for the course [insert course title].
The syllabus structure should include:
– Course title and general description
– Learning objectives and outcomes consistent with [indicate source of requirements]
– Weekly plan
– Teaching methods
– Assessment methods
– Required and supplementary literature
Prepare the document so that it can be easily modified by the instructor: clearly mark the sections where additional input can be added (e.g., [To be completed by the instructor]).
At the end, propose an alternative version of the syllabus in a project-based or case study–based format.
.

10.2. Creating Quizzes, Assignments, and Presentations

GenAI can also support the creation of assignments, quizzes, and presentations. In many of today's popular tools, developers are increasingly integrating AI-powered features that enable automation and assist in content generation. When designing assignments or quizzes, both general-purpose chatbots and specialized platforms can be used to generate materials and initial drafts of learning resources.

Table 10.1. Example Tools for Creating Quizzes

Tool	Availability	Key AI-Supported Features
www.questgen.ai		
Questgen	Free	Generates multiple-choice and true/false tests; creates questions from various sources (text, PDF, web, image, video). Supports export in multiple formats (Moodle, PDF).
www.revisely.com		
Revisely AI Quiz Maker	Free	Transforms notes, books, PDFs, and PowerPoint files into quizzes; supports the entire process (creation, editing, and assessment).
questionwell.org		
QuestionWell	Free	Creates, analyzes, personalizes, and exports materials aligned with curriculum requirements..
www.quillionz.com		
Quillionz	Free	Generates questions and summaries from text in four steps; designed as a teaching support tool.

Source: author's own elaboration

It is also worth noting that these and similar tools can often be integrated with Learning Management Systems (LMS) such as Google Workspace or Office 365. These platforms include features that enable educators to create assignments, monitor student progress, and use AI assistants such as Copilot or Gemini. They can also serve as valuable resources for designing presentations. Additionally, tools like Gamma (www.gamma.app) and Canva (www.canva.com) are highly useful. The latter is a powerful graphic and visual design platform equipped with AI modules that support the creation of documents, visual representations, video materials, and interactive content.

.

10.3. Metaprompts and Reflection on Learning

In the educational process, chatbots can also be used to support students' learning. According to Professor Joanna Mytnik, it is important to create spaces for reflection on both the benefits and challenges of using such tools. She recommends employing reflection worksheets that help learners organize their experiences while developing critical thinking and learning competencies (Mytnik, 2025).

Another valuable approach involves the use of *metaprompts* instructions that define the chatbot's communication style and tasks so that it can serve as an assistant in the learning process and perform dedicated educational functions.

An example of a metaprompt, ready to be adapted to individual needs, is provided below (CNE PG, 2024):

> *„You are a supportive teacher-tutor who helps the learner understand concepts, explains topics, and asks thoughtful questions. Begin by introducing yourself to the learner as their AI Tutor who is happy to answer any questions, and ask how they would like to be addressed. Ask only one question at a time.*
> *First, ask what the learner would like to know. Wait for the answer.*
> *Next, ask about their level of familiarity with the topic and their current level of knowledge. Wait for the answer.*
> *Then, ask what they already know about the chosen subject. Wait for the answer.*
> *Based on this information, help the learner understand the topic by providing explanations, examples, and analogies. These should be adapted to their level and prior knowledge. Offer explanations, examples, and analogies that clarify the concept and guide understanding.*
> *Lead the learner in an open and exploratory manner. Do not give immediate answers or full solutions to problems; instead, help them generate their own answers by asking guiding questions. Ask the learner to explain their reasoning. If they encounter difficulties or provide an incorrect answer, ask them to complete part of the task or remind them of the goal, and offer a helpful hint.*
> *If the learner corrects themselves, praise them and express genuine encouragement. If they struggle, motivate them and offer a few ideas to reflect on. When prompting the learner for more information, try to end your responses with a question that encourages further thinking.*
> *Once the learner demonstrates a satisfactory level of understanding for their stage of learning, ask them to explain the concept in their own words this is the best way to confirm comprehension or invite them to provide examples. When the learner shows they understand the idea, you may conclude the conversation by telling them you're available if they have further questions."*

Summary in chapter 10

Generative artificial intelligence opens new possibilities for creating and improving educational materials, enabling the rapid development of syllabi, case studies, quizzes, presentations, and multimedia content. Its use allows for greater diversity in teaching formats, better adaptation of materials to students' needs, and automation of time-consuming processes. At the same time, it is essential to maintain the critical role of the academic teacher who gives the materials their final form, ensures their substantive accuracy, and aligns them with learning objectives. AI should therefore be regarded as a supportive tool that enhances the efficiency and attractiveness of teaching but never replaces the educator's responsibility and pedagogical expertise.

11. Best Practices and Recommendations for Early-Career Researchers and Doctoral Students

The starting point for establishing good research practices among early-career scholars is provided by international institutional frameworks. This chapter draws on two key documents: the European Code of Conduct for Research Integrity (ALLEA, 2024) published by the Council of Europe, and UNESCO's Guidance for Generative AI in Education and Research (2023). Together, they provide a structured framework for academic and research work in the context of the dynamic development of artificial intelligence.

11.1. Balancing Efficiency and Integrity

R The European Code of Conduct for Research Integrity (ALLEA, 2024) argues that research integrity is fundamental to maintaining the credibility of the scientific system and its outcomes. It applies to all areas of academic and scientific life, including early-career researchers working under diverse institutional and legal arrangements. The Code serves as a framework for self-regulation within the research community.

The main principles of research integrity include (ALLEA, 2024):

- Reliability, encompassing quality at every stage of research planning, methodology, analysis, and resource use.
- Honesty, in developing, conducting, reviewing, reporting, and communicating research with transparency, fairness, and impartiality.
- Respect for research participants, the scientific community, research subjects, society, ecosystems, and cultural and natural heritage.

- Accountability for research at all stages from conception to publication including project management, supervision, mentoring, and the broader societal impact of research.

The Code pays particular attention to training, supervision, and mentoring, which are crucial for the professional growth of early-career researchers and doctoral students. It highlights that researchers at the beginning of their careers, often employed on short-term contracts, are especially vulnerable to pressures related to efficiency and productivity, which may compromise research integrity. Emphasis is placed on ensuring quality, reliability, and robustness of research outcomes, which ultimately provide greater long-term value even at the expense of short-term "efficiency."

Key integrity-promoting aspects that help maintain this balance include (ALLEA, 2024):

- Emphasis on reliability and quality assurance in research design, methodology, analysis, and documentation. Research must be conducted in a careful, transparent, and well-considered manner.
- Researchers should report results and methods, including the use of external services or AI tools, in accordance with disciplinary norms, allowing verification and, where possible, replication.
- Data access should follow the FAIR principles *Findable, Accessible, Interoperable,* and *Reusable* being "as open as possible, as closed as necessary."
- Authors must communicate accurately and honestly, disclosing assumptions, values, the robustness of evidence, uncertainties, and knowledge gaps. Publishing negative results is equally important as sharing positive findings.
- The Code explicitly identifies integrity violations such as fabrication, falsification, plagiarism, data manipulation, concealing AI use, "salami publishing," and selective citation. Avoiding these practices is essential for upholding genuine integrity over superficial productivity.

UNESCO's Guidance for Generative AI in Education and Research aligns closely with these principles while expanding the discussion to include risks specific to the digital age deepening digital divides, violations of intellectual property rights, biases, reduction of diversity and critical thinking, misinformation, and environmental costs (UNESCO, 2023).

Taken together, these guidelines emphasize that research should not be driven solely by performance metrics or efficiency areas where AI tools may offer superficial advantages. Instead, true academic value lies in creating conditions that allow researchers to slow down, reflect, and sustain quality. As Berg and Seeber (2016) argue, reclaiming time for thoughtful scholarship enhances not only academic well-being but also the intellectual rigor of research and teaching. Similarly, the *National Academies of Sciences* (NAS, 2015) stress that sufficient time allocation supports effective team coordination, reflective inquiry, and the responsible execution of research tasks.

11.2. Risk/Benefit Matrix for Different Stages of Research

K The concept of assessing and minimizing risk is strongly emphasized in the EU report, particularly in the section devoted to *safeguards*. The benefits of research are associated with the pursuit of knowledge, the advancement of understanding of the world, and the preservation of credibility and trust in science.

Key points regarding risks and benefits include:

- Researchers should identify and consider potential harms and risks associated with their studies and applications, and take steps to mitigate any negative impacts.
- Researchers, institutions, and organizations must adhere to relevant codes of conduct, guidelines, and regulations. They should treat all research participants and subjects (humans, animals, cultural heritage, the environment) with respect and caution, in accordance with ethical and legal standards.
- Appropriate care should be taken to ensure the health, safety, and well-being of communities, collaborators, and all individuals connected to the research process.
- Failure to comply with good research practices undermines research integrity, damages trust among scientists, erodes public confidence, wastes resources, and may expose participants, subjects, users, society, or the environment to unnecessary harm.

Based on established literature and institutional guidance, we have developed a risk–benefit matrix designed to support decision-making and quality control throughout the research process. For early-career researchers, it can serve as an orienting tool illustrating how, at different stages of research, generative AI may either enhance or compromise research integrity. It can also foster reflection by inviting researchers to compare their own practices with recognized standards.

The decision section of the matrix provides guidelines indicating the direction of appropriate actions. The table below is a proposed model not a replacement for critical judgment, but rather a tool to strengthen it.

The matrix follows the standard structure of the research process: conceptualization, project/protocol, data, analysis/code, writing, dissemination, and risk management, reflecting the classical framework described by Creswell & Creswell (2018).

Table 11.1. Risk and Benefit Analysis for the Use of Generative AI

Research Stage	Potential Benefits (AI)	Main Risks	Control Measures	Decision Threshold
1. Concept / Literature Mapping	Rapid review, summaries, topic maps	Hallucinations, incorrect citations, cognitive bias	Manual source verification; use of verified databases; audit notebook documenting decisions, actions, and sources used	Only if >80% of sources have DOI; otherwise conditional. (UNESCO, 2023)
2. Project / Protocol	Method triangulation, PRISMA/CONSORT checklists	"False authority" of models, methodological mismatch	Compliance with PRISMA/CONSORT checklists	Only after checklist compliance. (Page et al., 2021; CONSORT, 2025)
3. Data	FAIR-based data management templates, preliminary anonymization	Privacy issues, licensing, unauthorized data use by model	Institutional repositories; data management plan compliant with FAIR principles	Only when FAIR and data-processing requirements are met. (Wilkinson et al., 2016)
4. Analysis / Code	Code drafting, test generation, automated commenting	Computational errors, reproducibility debt	Version archiving, unit testing, computation logs, data/code preservation	Only with testing and version archiving. (Nosek et al., 2015)
5. Writing / Editing	Structural suggestions, drafting acceleration, language editing	Plagiarism, fabricated sources, non-academic style	Disclosure of AI use, full citation verification, prohibition of AI authorship	Only with disclosure and full verification. (COPE, 2023)
6. Dissemination / Graphics	Public summaries, visualization of findings	Copyright violations, contextual distortions	Review publisher policies; use of proprietary or open-access assets	Only in compliance with publisher policy. (Nature, 2023; Springer Nature, 2023)

7. Risk Managemen t	Profiling of risk networks and control dependencies	Underestimation of areas or cross-domain effects	Supervision, mapping, monitoring, crisis management procedures	According to the risk matrix (NIST, 2023)

Source: author's own elaboration

Of course, for early-career researchers, the support of mentors, supervisors, and the broader research community in which their development takes place is invaluable. Guidance from experienced scholars remains an essential and crucial element in helping young researchers cultivate their academic and teaching competencies, refine their methodologies, and strengthen their overall research practice.

11.3. Digital Competence Development Plan

Digital competence encompasses a broad spectrum that integrates knowledge, skills, and attitudes, extending far beyond the narrow interpretation of computational thinking or technical proficiency in using digital devices. It is recognized as one of the eight key lifelong learning competences (European Commission, 2006) and represents a set of abilities enabling individuals to use technology effectively to optimize daily life (Zhao et al., 2021). The European Commission defines it as the confident, critical, and responsible use of digital technologies for work, leisure, and learning (Education and Training, 2019).

In the area of knowledge, early-career researchers should understand how digital technologies including those powered by artificial intelligence can support teaching, research, communication, and creativity, while also being aware of their limitations and potential risks. This awareness extends to ethical and regulatory dimensions, which have been repeatedly emphasized in this publication (Education and Training, 2019).

In the area of skills, researchers at the beginning of their academic path should be able to use digital technologies for collaboration, creativity, project management, and educational activities. These skills include the ability to access, evaluate, create, code, and share digital content (Education and Training, 2019).

In the area of attitudes, young scholars should cultivate a reflective and critical mindset, combined with openness and a value-oriented approach to digital opportunities. Developing responsible and safe digital practices is essential for sustaining trustworthy and ethical engagement with technology (Education and Training, 2019).

For teachers and academic staff, digital competence involves not only the critical and responsible use of ICT resources but also the ability to assess, collaborate, and provide feedback to students within contemporary digital learning environments (dos Santos et al., 2023).

In research contexts, the ability to manage data in a structured and secure way while ensuring its ethical and informed use has become a cornerstone of nearly every field. Proper archiving, publishing, and enabling data reuse are key to ensuring the integrity, credibility, and reproducibility of scientific work (dos Santos et al., 2023).

The European Digital Competence Framework (DigComp), developed by the European Commission's Joint Research Centre, outlines six levels of proficiency, ranging from basic to pioneering. These levels are aligned with the nomenclature of the Common European Framework of Reference for Languages *(CEFR)*, using designations from A1 to C2. Progression through these stages represents a continuous learning process one that now increasingly includes the effective and ethical integration of generative AI. The framework's structure is presented in Table 11.2 (Vuorikari et al., 2022).

Table 11.2. Digital Competence Development Model

Level (CEFR)	**Description of Criteria (DigCompEdu)**	**Actions to Achieve the Level**	**Level of GenAI Use**
Newcomer (A1)	Basic awareness of technological possibilities; irregular and fragmented use, mainly for administrative and simple teaching tasks.	Participation in introductory training; use of basic tools (e.g., presentations, e-learning platforms).	Experimental use of AI for simple prompts (e.g., improving language in emails, generating topic lists).
Explorer (A2)	Interest in exploring digital tools and using them in selected areas; activity remains unsystematic.	Incorporating digital tools into selected teaching processes or research projects; learning from practitioners' experiences.	Use of GenAI for literature searches, creating short summaries, and drafting quizzes or syllabi.
Integrator (B1)	Experimenting with technologies in various contexts to achieve different goals; integrating	Creating own online learning materials, applying blended learning, and planning courses using Learning	Systematic use of GenAI as a tool supporting content creation and data analysis.

	them into teaching and research practice.	Management Systems (LMS).	
Expert (B2)	Critical and informed use of a wide range of technologies; matching tools to specific goals and contexts.	Participation in projects implementing digital technologies at the university; mentoring other staff members.	Critical application of GenAI for text editing, qualitative analysis, and preparing visualizations or simulations.
Leader (C1)	Comprehensive and strategic approach; inspiring others; continuous improvement and pursuit of new, efficient solutions.	Designing digital competence training, publishing best practices, leading teaching and research teams.	Developing metaprompts and GenAI work strategies; conducting training for doctoral students and colleagues; integrating GenAI into team and research projects.
Pioneer (C2)	Innovative, experimental approach; creating new educational and technological models; implementing and disseminating unique solutions in academia.	Initiating research projects on digital innovation, engaging in international collaboration, developing institutional recommendations.	Experimenting with multimodal AI, creating proprietary AI tools, integrating AI into research and teaching as a component of new methodologies.

Źródło: Author's own work based on *DigCompEdu*.

Summary of Chapter 11

This sixth chapter emphasizes that the key challenge for early-career researchers lies in maintaining a balance between the efficiency offered by artificial intelligence and the integrity of research. International guidelines (UNESCO and the Council of Europe) stress that productivity pressures must not compromise research quality honesty, transparency, accuracy, and accountability for results remain fundamental. AI tools can support every stage of the research process; however, their use requires critical evaluation of sources, data verification, protection of privacy, and adherence to ethical and legal standards. A useful aid in this regard is the proposed risk–benefit matrix, which facilitates responsible decision-making.

At the same time, this chapter highlights the importance of developing digital competences not only technical proficiency but also critical thinking, communication, creativity, and collaboration. These skills should evolve gradually: from basic awareness of digital tools, through systematic use of AI in teaching and research, to innovative models of scholarly work. Altogether, the discussion underscores that the responsible integration of AI into academic practice requires not only technical fluency but also ethical reflection, transparency, and ongoing support from mentors and institutions.

Summary

In writing this monograph, the authors sought to create a practical guide that doctoral students and early-career researchers could readily turn to. It brings together definitions, perspectives, models, and practical examples designed to serve the broader community of emerging scholars. The book's use is intended to support a structured and holistic application of generative artificial intelligence, while fostering awareness of its limitations. In line with current research agendas and universal ethical frameworks, readers are encouraged to pursue continuous professional growth and the expansion of their competences beyond what is covered in these pages. The pace of technological change and uncertainty about future directions make it impossible to predict how AI tools will ultimately shape academic institutions. Nonetheless, the values emphasized throughout this volume remain enduring providing a bridge between the present and the rapidly unfolding future.

Part One organized key concepts and theoretical contexts, situating AI especially generative models within the methodology of contemporary research. It demonstrated the synergy between humans and computational systems in the learning process, referring to cyclical models of research activity, and identified key limitations such as hallucinations, bias, explainability issues, and ethical-legal risks. It also discussed methodological developments (dynamic reviews, RAG integration, growing demands for transparency) and outlined the convergent positions of academic publishers regarding disclosure and author accountability. The section was grounded in current practice and regulation, underscoring the necessity of continuous verification of policies and standards.

Part Two served as a practical, operational guide. It proposed frameworks for prompt engineering and step-by-step workflows (from data extraction to result verification), offered examples of AI-supported writing and editing, and introduced automation scenarios ("Sheets → AI → report") alongside best practices for creating educational materials. The included verification checklists for content and references emphasize that while generative tools can accelerate academic work, they do not eliminate the need for critical evaluation, procedural replicability, or bibliographic accuracy. The chapter also marked the boundaries of AI-content detection, recommending that such results be treated as supporting indicators rather than definitive judgments.

Throughout the monograph, a pragmatic stance was adopted: AI is positioned as part of the research infrastructure enhancing analysis, synthesis, and scholarly communication yet never replacing human responsibility for conceptualization, methodological choice, and interpretation. Accordingly, the authors stressed human-in-the-loop practices: documenting tool usage, implementing cross-verification, and transparently disclosing the role of AI models within academic texts. This approach aligns the pursuit of efficiency with the imperatives of quality and integrity.

The recommendations distilled from the analyses and examples can be summarized in three overarching principles:

1. Transparency - all data, decisions, and tools should be described in ways that enable auditing and traceability.
2. Methodological adequacy - AI should be employed only where it brings measurable value, not to create a false impression of precision.
3. Long-term competence development - training in AI-assisted writing, transversal skills, and team collaboration should be systematically planned and evaluated as part of every researcher's toolkit.

This monograph does not claim to exhaust the topic. Both AI models and publishing and legal frameworks continue to evolve rapidly. Therefore, regular updating of procedures in line with disciplinary, journal, and institutional requirements is essential, alongside the development of open-science, licensing, and data-protection practices. The proposed methods particularly those concerning literature reviews, automation, and educational design are adaptable templates that can be tailored to different research domains.

In times of technological uncertainty, stable reference points remain the core values of research integrity: credibility, honesty, respect, and accountability. These principles reaffirm that humans must remain the ultimate decision-makers, while AI should be regarded as a resource subject to oversight, quality control, and transparency. Such a paradigm of cooperation allows researchers to harness the potential of generative tools without undermining the essence of scholarship the pursuit of truth, understood as a cognitive, social, and ethical endeavor.

Thus, this monograph may serve as a compass: it organizes foundations, proposes methods, and offers actionable models without replacing critical reflection or academic autonomy. Implementing its recommendations into everyday practice contributes to building a research and learning environment in which generative AI becomes a means of amplifying scientific agency and reach, rather than a substitute for human judgment.

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