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(Research Article)

University as an Orchestrator of Ecosystemic Learning: Integrating LLM Assistants and Prompt Engineering into Core Disciplines and Assessing Their Impact on the Productivity of Students and Faculty

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Abstract

The article analyzes the transformation of higher education under the influence of generative Artificial Intelligence and proposes a conceptual framework for the university-orchestrator model, which deliberately governs the emergent educational ecosystem. The aim of the study is to construct and theoretically substantiate this model by examining the key activity domains of the university: the incorporation of prompt engineering as a new academic literacy into curricula, the assessment of the impact of large language models (LLM) on the productivity of learners and faculty, and the management of associated risks. The methodological base includes a systematic literature review and a content analysis of industry reports. The results show that the widespread use of LLM assistants (more than 86% of students) has generated a shadow ecosystem that requires universities to shift from reactive measures to proactive orchestration. It is established that LLM tools increase productivity: learning outcomes improve by up to 30%, and faculty save more than two hours per week. At the same time, this effect is mediated by the emergence of new invisible work for verification and editing. In conclusion, it is argued that effective orchestration is a necessary condition for maximizing the positive effects of LLM while simultaneously mitigating technological, pedagogical, and ethical risks. The information presented will be of interest to university administrators, program directors, and researchers studying the societal impact of AI.

Keywords: Ecosystemic Learning; Large Language Models (LLM); Generative Artificial Intelligence; Prompt Engineering; Higher Education; Student Productivity; Faculty Workload; Pedagogical Integration; Digital Literacy; Risk Management

1. Introduction

Contemporary higher education is undergoing a profound paradigmatic shift, triggered by the rapid development and ubiquitous integration of generative Artificial Intelligence. Technologies based on large language models: ChatGPT, Copilot, Gemini, have ceased to be niche solutions and have become an infrastructural technological wave that is radically changing the logic of the economy and societal institutions [11, 13]. The university sector is not only not an exception but in fact stands at the forefront of this transformation.

The relevance of the study is determined by the unprecedented pace and scale of the adoption of LLM assistants in academic practice. Data for 2024–2025 record near-universal use: up to 92% of students in the United Kingdom and 86% of learners worldwide regularly turn to AI in educational activities [2]. The adoption dynamics among faculty and administrative teams are comparable in pace and reach 84% [2]. These indicators suggest that this is not a short-term trend but an established new reality requiring immediate strategic reflection from the university community. The long-term and capital-intensive nature of the transformations is confirmed by forecasts of exponential growth of the AI-in-

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education market: according to estimates, by 2030–2034 its volume will amount to between 32 and 112 billion US dollars [3].

Amid the density of the publication landscape, spanning ethical issues and tool development through to impacts on academic integrity, a substantial lacuna persists in the literature [4, 8]. There is no cohesive conceptual foundation in which the university is defined not as a passive observer or reactive regulator, but as an active orchestrator — the central actor deliberately designing, aligning, and governing a new, complex educational ecosystem built on the symbiosis of human and Artificial Intelligence [7, 11]. Existing studies mainly address questions of what to use and how to apply, leaving unresolved the key question of who should govern and in what manner the multilayered and often emergent process of change should be managed. Current institutional responses of many universities are predominantly defensive and focused on policies to prevent plagiarism and regulate the use of AI [2, 6]. However, the widespread adoption of practices and the documented growth in productivity render such a stance consistently untenable. The shift from a reactive posture to a proactive orchestration model constitutes a strategic imperative [4, 5].

Aim

- **The aim** of the study is to develop and provide the theoretical and methodological justification for a conceptual model of the university-orchestrator through analysis of its key domains of activity: integrating prompt engineering into curricula, assessing the impact of LLMs on the productivity of students and faculty, and building mechanisms for managing associated risks.
- **The scientific novelty** of the work is determined by the fact that, for the first time, a model is proposed that conceptualizes the university as the central actor orchestrating the educational ecosystem under conditions of pervasive integration of LLM assistants.
- **The author's hypothesis** is as follows: effective orchestration by the university of the processes of implementing LLMs and prompt engineering including the development of institutional policies, curriculum renewal, and targeted staff training leads to a measurable increase in the aggregate productivity of participants in the educational process (students and faculty) and enhances the university's competitiveness while associated risks persist.

2. Materials and methods

The study was conducted within an interdisciplinary paradigm; its methodological framework integrates qualitative and quantitative procedures for processing data from heterogeneous sources. The methodological design rests on two complementary approaches.

First, a systematic literature review was conducted.

Second, content analysis of industry reports was applied. To extract current statistics, market forecasts, and macrotrends, analytical reports and reviews of leading consulting and research organizations, including McKinsey, as well as specialized technology firms for market monitoring such as Gartner, MarketsandMarkets, and Mordor Intelligence were analyzed. This approach provided the study with a verifiable quantitative basis necessary to evaluate the scale and dynamics of the phenomenon under consideration.

The combination of these approaches made it possible not only to synthesize existing scholarly knowledge but also to align it with current market and technological trends, which is a necessary condition for developing a holistic and practice-oriented model of the university-orchestrator.

3. Results and discussion

The body of current empirical research shows that the integration of LLMs into higher education has already moved beyond pilot initiatives and entered a phase of large-scale, albeit in many respects unmanaged, diffusion. The level of student use of AI assistants has reached — 86–92% [2], which de facto makes these tools an infrastructural component of the learning environment on a par with text editors and search engines.

Against the backdrop of rapid bottom-up diffusion, a substantial gap in institutional readiness is evident. Only 57% of universities declare AI as a strategic priority, and only 39% have formalized and implemented regulations for its use [2]. The mismatch between practice and the normative framework gives rise to a shadow AI ecosystem in which students and instructors, through trial and error, construct their own procedures, ethical guidelines, and quality criteria.

This amplifies the risks of academic dishonesty, the spread of inaccurate data, and the deepening of digital inequality. Consequently, the task of the university is not to create an ecosystem from scratch, but to legitimize, institutionally integrate, and purposefully govern the practices already in place. Assuming the role of orchestrator becomes a strategic imperative that transforms spontaneity into a manageable and productive system.

The scale of the transformation is corroborated by financial trajectories. A comparison of estimates by leading research agencies (Table 1) shows a consensus regarding the exponential dynamics of the AI-in-education market: despite differences in absolute values, all forecasts converge on a compound annual growth rate (CAGR) in the range of 17,5–43,8%. The key drivers consistently cited are personalized learning, intelligent tutoring systems, and process automation, indicating a shift of emphasis from administrative solutions toward pedagogical technologies.

Table 1 Comparative analysis of AI market growth forecasts in education (compiled by the author based on [5, 6, 7, 17, 18]).

Market estimate in 2024 (USD billion)	Forecast for 2030 (USD billion)	Projected CAGR (%)	Key growth drivers
2,21	5,82	17,5	Personalized learning experience, deployment of e-learning platforms, data analytics.
4,17 (in 2023)	53,02	43,8	Intelligent adaptive learning, IT infrastructure development, vendor–university collaborations.
5,88	32,27	31,2	Demand for personalized learning, growth of virtual learning environments, hybrid models.
4,7	26,43 (by 2032)	37,7	Digital transformation, deployment of content delivery systems, growth of machine learning.
4,79	41,01	42,8	Digital literacy policies, adoption of cloud technologies, measurable student outcomes.

The graphical representation of data on the degree of AI adoption (Fig. 1) convincingly reveals an asymmetry between students' everyday practices and the level of instructors' engagement. The resulting imbalance underscores once again the need for targeted university actions focused on staff training and support.

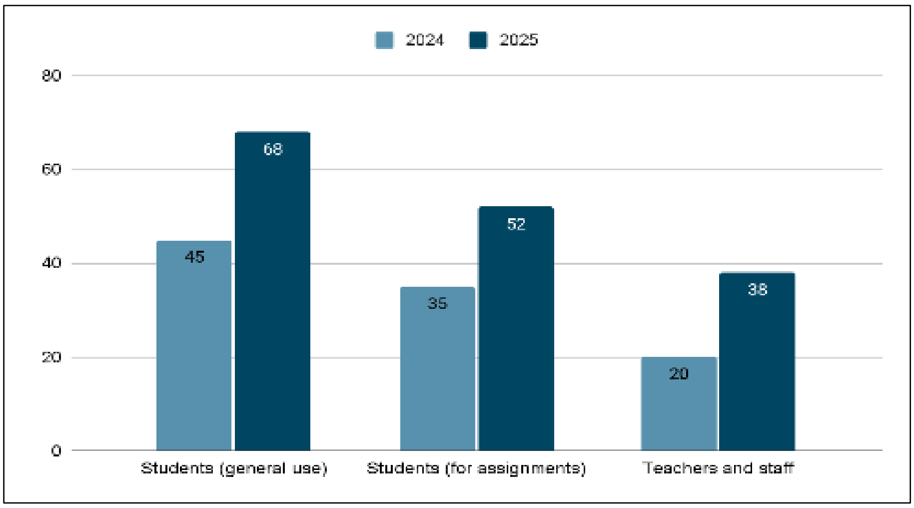

Figure 1 Dynamics of the implementation of generative AI in higher education (2024-2025) (compiled by the author based on [2])

It is further necessary to consider prompt engineering (PE), which should be construed as a new literacy of the 21st century—an interdisciplinary meta-skill critically important for successful academic and professional activity [16]. This is not reducible to asking a chatbot a question but constitutes a complex process that includes understanding the model architecture, operationalization of context, iterative refinement of formulations, and critical validation of the resulting conclusions [20, 21].

An analysis of PE use across disciplinary domains reveals its high adaptability.

In STEM fields (Science, Technology, Engineering, and Mathematics), PE is applied predominantly to clearly specified tasks. Priority is given to accuracy, reproducibility, and efficiency. Typical cases include synthesis and debugging of code, execution of complex computations, analysis of datasets, modeling of physical processes, and solving standard engineering problems. In such contexts, the prompt in form and function is close to a technical specification or a programming-language command [15, 16].

In the humanities and the social sciences, PE serves more open, interpretive tasks, where emphasis shifts to nuance, context, plurality of perspectives, and creativity. Characteristic examples include semantic processing of large text corpora, generation of research hypotheses, comparative analysis of philosophical concepts, synthesis of historical sources, and identification of latent themes in literary works. Here the prompt functions as a tool for research dialogue rather than as a mechanism for obtaining a single answer [9, 10].

This dichotomy underscores the need to develop a comprehensive competency model in the field of PE (Fig. 2) that takes into account universal principles and disciplinary specificity.

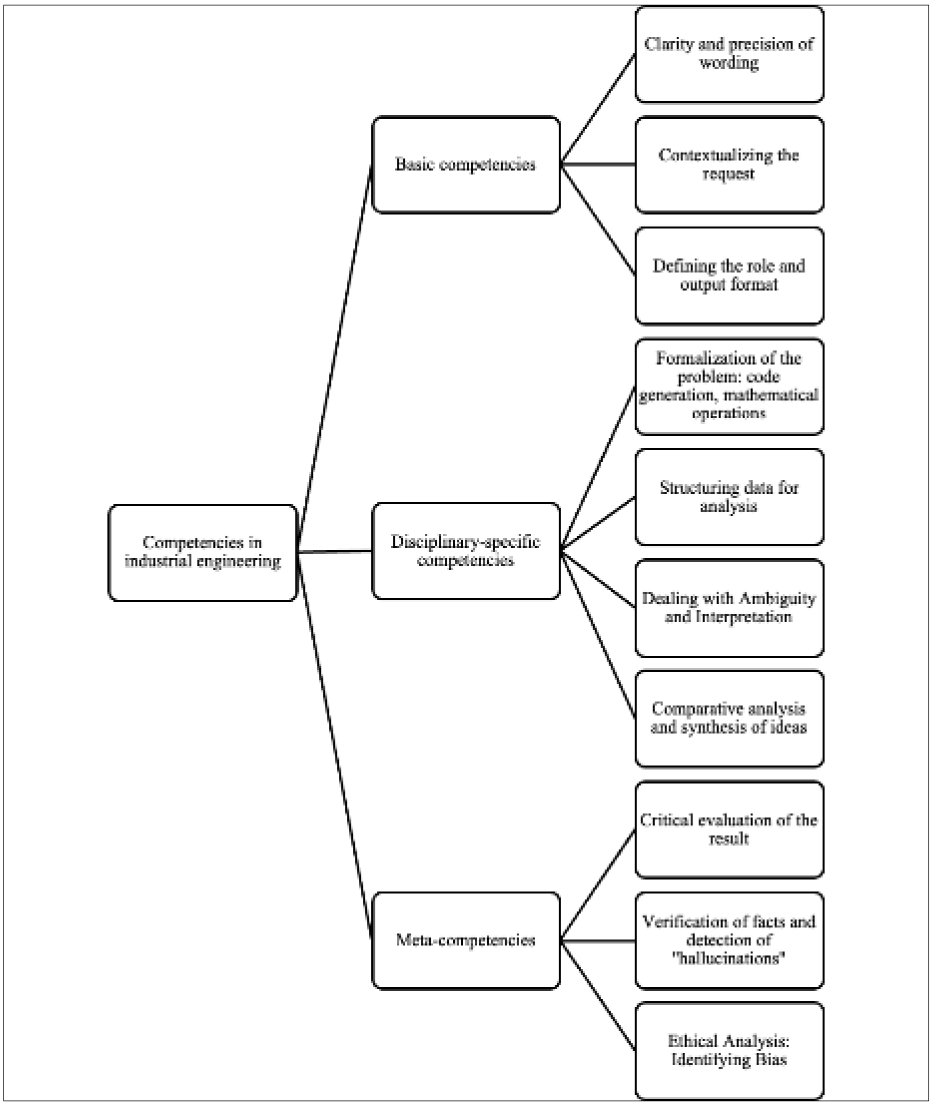

Figure 2 Conceptual model of competencies in the field of industrial engineering (compiled by the author based on [9, 10, 14, 21])

The significance of PE lies in its intrinsic integration of two typologically different cognitive modes, traditionally separated within the framework of the two cultures — the natural-scientific and the humanistic. On the one hand, an effective prompt relies on logical composition, formal precision, and algorithmic discipline characteristic of programming. On the other, it requires deep command of context, sensitivity to semantic nuance, rhetorical competence, and the ability to articulate complex ideas in natural language [12, 13]. There has long been a demand to embed humanistic knowledge in engineering education to cultivate systems thinking and a social vision of technology. By teaching students prompt engineering, the university in effect trains both structurally formal and context-sensitive thinking simultaneously. In this way, PE functions not merely as a new skill but as a specific pedagogical instrument of interdisciplinary integration that allows the aforementioned divide to be overcome in practice.

The integration of LLM assistants exhibits a measurably positive effect on the productivity of both students and instructors, although the profile of this effect differs and has its own nuances. With respect to students, effectiveness is recorded across a set of quantitative and qualitative indicators. Quantitative data show that personalized AI-supported instruction can improve academic outcomes by up to 30% relative to traditional formats through adaptation of pace and difficulty level to individual trajectories. In addition, a pronounced increase in motivation is observed: 75% of students report greater engagement in personalized AI environments [4]. One of the most telling indicators is a 70% increase in course completion rates, especially salient for online and blended formats. Qualitative evidence from self-reports corroborates these trends: learners note substantial time savings and quality gains when using AI to clarify difficult concepts, conduct brainstorming, synthesize sources, and structure argumentation [2].

For instructors, the primary effect manifests as a reduction of routine workload. AI tools make it possible to automate or sharply accelerate resource-intensive operations: construction of instructional materials (lecture plans, presentations, test items), development of assessment rubrics, and the provision of basic feedback on student work. By estimates, active AI users save more than two hours of work time per week [2]. Concrete practices confirm this dynamic: in medical education, generative AI is employed to construct simulations of clinical cases, which eases the load on the professoriate while preserving the high didactic value of the content [16, 19].

Nevertheless, productivity gains from the adoption of LLMs are neither linear nor guaranteed. A productivity paradox is observed: a tool intended to save time constructs new forms of invisible work that partially erode the gains. Users report acceleration in task execution, yet simultaneously note that AI-generated text is often unsatisfactory and requires refinement and post-editing [13]. Given the propensity of LLMs for factual errors, hallucinations, and bias [8], the stages of verification and critical appraisal cease to be optional and become mandatory elements of the workflow. As a result, the actual efficiency gain is the difference between the time saved on generation and the time spent on verification, correction, and integration of the output. This marks a fundamental shift in the nature of academic labor. The role of the university-orchestrator here is not merely to teach the use of AI, but to develop competencies for managing the more complex cycle generation — verification — integration.

Despite the evident potential, full-scale and coordinated integration of LLMs into the educational ecosystem is associated with a broad set of risks and barriers. For effective orchestration, it is necessary to systematize them and define strategies for minimization.

4. Conclusion

The results obtained make it possible to articulate conclusions that simultaneously confirm and refine the initial hypothesis.

First, the introduction of LLM assistants into higher education is not yet another technological modernization but a qualitative paradigmatic shift. The scale and pace of change compel universities to move from a passive-reactive stance to the preemptive role of the orchestrator: the central actor that deliberately designs, guides, and aligns the socio-technical educational ecosystem of human–AI interaction.

Second, prompt engineering has taken shape as a new interdisciplinary academic literacy. It is a foundational competence for the responsible and effective use of AI. Its integration into curricula across all programs becomes a university priority and should account for disciplinary specificities while simultaneously developing technical skills and humanistic practices of communication with LLM.

Third, the impact of LLM on the productivity of students and faculty is measurable and on the whole positive. At the same time, the effect is nonlinear and mediated by the growth of invisible work associated with verification, critical appraisal, and editing of generated materials. Consequently, the task of the university is not to limit itself to providing access to tools but to shape more sophisticated workflows that increase returns and reduce the costs of quality control.

Fourth, effective orchestration of the new ecosystem is impossible without comprehensive risk management. The university requires a multilevel system of measures to minimize technological risks (errors, biases), pedagogical risks (weakening of critical thinking), and ethical-institutional risks (data confidentiality, inequality). This implies developing clear policies, launching staff upskilling programs, and updating pedagogical approaches and assessment procedures.

Thus, the analysis conducted confirms the authorial hypothesis: purposeful and comprehensive orchestration of LLM integration is a necessary condition for realizing their positive potential for increasing the productivity and competitiveness of universities, as well as for the effective neutralization of accompanying risks.

The practical significance of the work lies in the fact that its results and the proposed model of the university-orchestrator can serve as a basis for developing long-term digital transformation strategies at the level of managerial decision-making. Program leaders obtain tools for modernizing curricula and introducing courses that develop AI literacy. Faculty members obtain guidance for adapting pedagogical practices and assessment methods to the new conditions.

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