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THE CHANGING ROLE OF THE RESEARCHER: FROM SPREADSHEETS TO LARGE LANGUAGE MODELS

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Abstract. *The rapid evolution of data analysis tools has led to a fundamental transformation of the researcher's role in scientific inquiry. This article examines how the shift from spreadsheet-based analysis to statistical computing and, more recently, to artificial intelligence agents driven by large language models (LLMs), has altered analytical responsibilities, expertise, and epistemic authority. Instead of focusing solely on technical capabilities, the research highlights the transformation of the role: from operator to programmer-methodologist, to manager and validator of machine-generated insights. The article argues that contemporary research increasingly depends on skills related to critical evaluation, bias detection, methodological auditing, and ethical judgment. This shift marks a transition from creating analytical logic to managing and verifying it. Understanding this transformation is crucial for maintaining scientific rigor, transparency, and accountability in AI-augmented research environments.*

Keywords: *researcher role, data analysis paradigms, spreadsheets, statistical computing, large language models, AI agents, bias.*

Introduction.

The history of scientific research is inextricably linked to the evolution of analytical tools. Each major technological shift has changed not only the ways in which data is processed, but also how researchers think, reason, and respond to results. For much of the late 20th century, spreadsheets served as the dominant analytical tool, emphasizing accessibility and manual control. Further developments in statistical computing have introduced algorithmic rigor and formalized methodological responsibility. Today, the integration of large-scale language models and artificial intelligence agents is a further transformation in which analytical thinking is partly delegated to autonomous systems. This progress requires a rethinking of the role, competencies, and responsibilities of the researcher in modern scientific workflows.

Paradigm I: The researcher as operator (spreadsheet-based analysis). In the spreadsheet paradigm, the researcher primarily functioned as an operator. Analytical

logic was built manually using cell-level formulas, direct data manipulation, and visual inspection of results. The researcher maintained complete control over the calculations, but often without formal methodological guarantees. While this paradigm offered rapid exploration and accessibility, it placed almost complete responsibility for correctness on manual actions (Panko, 2018). Common consequences included errors, hidden dependencies, and a lack of reproducibility. The researcher's expertise was more practical than methodological, focused on tool usage rather than statistical theory.

Paradigm II: The researcher as a programmer-methodologist (statistical computing). The transition to statistical computing environments fundamentally changed the role of the researcher. Analytical logic became explicit, encoded in scripts that obeyed statistical theory and computational rules. The researcher took responsibility not only for conducting the analysis, but also for choosing appropriate models, testing assumptions, and ensuring the reproducibility of the results. This paradigm increased methodological rigor and transparency, but required a much higher level of cognitive and technical skills. The researcher became a programmer-methodologist, combining subject knowledge with formal statistical and computational skills (Peng, 2011; Kitchin, 2014).

Paradigm III: The Researcher as director and validator (LLM-Driven AI Analysis). The emergence of LLM-driven AI agents introduces a fundamentally different role for the researcher. In this paradigm, analytical logic is no longer solely created by a human expert, but is partially generated by autonomous systems through natural language interaction (Brown et al., 2020; Bommasani et al., 2021). As a result, the researcher increasingly functions as a director and validator, rather than a direct producer of analytical code or models. The primary responsibilities shift to evaluating AI-generated results, identifying biases, auditing methodological validity, and ensuring ethical compliance (Bender et al., 2021; Ji et al., 2023; Tumanov, 2025). While this paradigm dramatically increases the speed and accessibility of analysis, it also introduces epistemic uncertainty, making oversight a central element of scientific practice.

Across three paradigms, the researcher's role evolves from operational execution to methodological construction and, finally, to epistemic management. This transformation reflects a broader redistribution of responsibility, rather than its elimination. As analytical systems gain autonomy, the researcher's responsibility becomes more abstract, but at the same time more critical. The ability to question, verify, and contextualize machine-generated insights becomes a defining competence of modern scientific work.

Implications for scientific practice. The growing reliance on AI systems requires new standards of training, assessment, and governance. Researchers must develop critical appraisal, bias mitigation, and ethical thinking skills in addition to traditional statistical knowledge. Hybrid analytical systems that combine AI-powered automation with classical human verification and control are needed to maintain scientific integrity in the context of AI.

Summary and conclusions.

We examined the transformation of the researcher's role across three main paradigms of data analysis: spreadsheets, statistical computing, and LLM-based artificial intelligence agents. This evolution was shown to represent a shift from creating analytical logic to evaluating and managing it. The modern researcher increasingly acts as a supervisor, validator, and ethical steward of machine-generated insights. These findings underscore the need for hybrid methodological approaches that maintain accuracy, transparency, and accountability as analytical autonomy continues to expand.

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MODELING OF THE AUTOMATIC TEMPERATURE REGULATION SYSTEM IN THE FIRING ZONE OF A TUNNEL FURNACE

МОДЕЛЮВАННЯ САР ТЕМПЕРАТУРИ У ЗОНІ ВИПАЛУ ТУНЕЛЬНОЇ ПЕЧІ

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Анотація. Розглянуто задачу моделювання системи автоматичного регулювання температури у зоні випалу тунельної печі як актуальну проблему підвищення ефективності автоматизованих систем управління технологічними процесами. Визначено передаточну функцію об'єкта з урахуванням запізнювання та розраховано оптимальні налаштування ПІД-регулятора. Проведено аналіз перехідного процесу, за результатами якого підтверджено стійкість системи та відповідність показників якості регулювання заданим вимогам.

Ключові слова: системи автоматичного регулювання, тунельна піч, моделювання, ПІД-регулятор.

Abstract. The problem of modeling the automatic temperature control system in the firing zone of a tunnel kiln is considered as a topical problem of increasing the efficiency of automated process control systems. The transfer function of the object is determined taking into account the delay and the optimal settings of the PID controller are calculated. The transient process is analyzed, the results of which confirm the stability of the system and the compliance of the control quality indicators with the specified requirements.

Key words: automatic control systems, tunnel kiln, simulation, PID controller.

Підвищення ефективності АСУТП є одним із фундаментальних завдань теорії управління. На даний момент питання розробки системи автоматичного регулювання температури у зоні випалу тунельної печі вивчено недостатньо, тому це є актуальною та перспективною задачею. Також це є актуальною проблемою у багатьох галузях промисловості для оптимізації процесів, підвищення продуктивності, якості та безпеки, мінімізації витрат.