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Disruptiveness of Artificial Intelligence in the Digital Transformation Era

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Abstract: Artificial intelligence (AI) and machine learning (ML) alike have become central to modern digital infrastructures, driving disruptive transformations in decision-making, workflows, and socio-technical systems. Beyond algorithmic performance, their impact stems from integration into complex ecosystems spanning smart infrastructures, industry, and services. While enabling autonomous, data-driven solutions, their adoption raises challenges related to transparency, risk, and governance. Addressing fragmented research, this article provides an integrated literature review that synthesizes key directions, applications, and implementation challenges, offering a systemic perspective on AI and ML as drivers of emerging disruptive technologies. With the use of a popular measurement application, called SEMrush, we managed to analyse and see the tendencies of AI usage and search-pattern to further and better understand how this phenomenon makes increasing appearance in daily lives, starting from normal usage for daily users or normal consumers, to well-established companies that feel the need to enhance themselves through modern means and sophisticated paths.

Keywords: artificial intelligence, technology, digital transformations, algorithms, applications

Introduction

Artificial intelligence (AI) and machine learning (ML) have moved beyond the status of experimental technologies to become integral components of contemporary digital infrastructures. Their use in information systems, organizational processes, and public services has led to the emergence of solutions that are not limited to optimizing existing activities, but influence the way decisions, workflows, and interactions between human and technological actors are designed. AI and ML are frequently associated with the development of disruptive solutions, through their ability to restructure established practices and generate new forms of value.

The disruptive nature of AI and ML-based solutions cannot be explained solely by algorithmic performance or the evolution of computing capabilities; it is closely linked to how these technologies are integrated into complex socio-technical ecosystems, where data, digital infrastructures, and organizational decisions influence each other. AI applications in areas such as smart digital infrastructures, cybersecurity, advanced industries, and professional services illustrate that the transformations produced are structural in nature, affecting system architectures, professional roles, and business models (Bratianu, 2025; Bratianu, Bejinaru & Banciu, 2026). ML is a subdomain of AI that allows systems to identify patterns, generate predictions, and adapt based on data without

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being explicitly programmed. The integration of ML into distributed solutions, such as the Internet of Things (IoT), edge computing, or cyber-physical systems, supports the emergence of intelligent architectures capable of functioning autonomously in dynamic environments. They are becoming enabling technologies for digital transformation, impacting the way contemporary IT systems are designed and operated.

At the same time, the expansion of intelligent solutions in critical contexts brings to the fore a series of challenges related to the transparency of automated decisions, uncertainty management, data protection, and institutional accountability. The use of AI and ML in distributed or autonomous systems requires careful analysis of the associated risks and the conditions under which these technologies can be implemented in a sustainable manner.

Disruptive AI-based solutions should be understood not only as technological achievements, but as socio-technical phenomena that involve trade-offs, organizational adaptations, and appropriate governance frameworks. Basically, it is about people and not just a code, through a sociological lens/perspective, because AI does not just simply exist, but rather create various connections between people, how they see and attribute value to their shared and individual expertise and experiences, and how they feel about their job stability and security, it is more like a culture shift directly but also an immense software upgrade. There are, however, trade-offs, such as giving up on certain things as humans for AI generated content or aspects. Here, we can stress the fact that creativity usually is bland, or, ironically, „artificial" when it is attributed to us by AI, same as transparency, because we do not know exactly how AI really „find" that information, and we start to question ourselves and AI's trustworthiness. At the same time, AI does not just replace manual labor, each company needs to reinvent itself and rewrite the "how-to" book, specific to that organization. It implies readying employees and changing their work pattern because AI turned into a „coworker", as such, organizations don't just „buy" AI software/licenses, they reinvent themselves, with the goal of continuous progress. Lastly, ethics play a big role in AI infrastructures, because at times, AI can certainly generate false positives, or it starts to make biased decisions. As such, inside of the company nobody knows who to blame or if there is anybody to blame and how they manage the situation. Nobody can say for sure that „AI is responsible for this…we must sanction it, we need to punish it disciplinarily", since that specific decision has been made by a piece of software that does not fall into a specific „signed contract" or „rational existence", that can be in any way, shape or form sanctioned. We cannot sanction anything or something abstract, so this poses as, still, a gray zone that needs to be cautiously observed and taken care of, monitored. As for ML (Machine Learning), which is a subset of AI, it is undoubtedly intertwined and linked to AI, such as AI being a driver and ML being the car being driven. ML works through AI by using algorithms to find patterns in data. To use ML effectively, it needs high-quality data; otherwise, it can be, and most of the time it will be, useless. Furthermore, human biases remain, complex models cannot be, as aforementioned, „punishable" for a bad decision, and the inexplainable factor of „why" ML made that decision, which is often impossible to describe or know, and this is an immense flaw in fields such as medicine. Lastly, AI can simply not understand the world as humans do, while AI can certainly be the best master at playing cards, it has no idea that those cards can not be eaten.

Although the literature offers a considerable amount of research on AI and ML applications, these contributions are often fragmented, either by focusing on specific areas or by emphasizing isolated dimensions, such as algorithmic performance or operational efficiency. This fragmentation limits our understanding of the mechanisms through which AI and ML contribute to the emergence of disruptive solutions at the systemic level, through the interaction between technologies, infrastructures, and decision-making processes. Based on these considerations, this article aims to analyze the role of artificial intelligence and machine learning in the development of disruptive solutions through an integrated review of literature. The objective is to highlight the main research directions, the types of solutions analyzed, and the recurring challenges associated with implementation in real contexts, thus contributing to a coherent perspective on the position of these technologies within the landscape of emerging and disruptive technologies. The objective is to identify key research directions, categorize the types of solutions examined, and determine recurring real-world implementation challenges through SEMrush-based search and analytical insights, thereby offering a coherent perspective on how these technologies position themselves within the broader landscape of emerging and disruptive innovations.

Literature review

Specialized literature increasingly treats artificial intelligence (AI) and machine learning (ML) as technologies capable of generating structural transformations in multiple economic and social fields. Initially analyzed as automation or decision-support tools, these technologies are now viewed in a broader context, highlighting their potential to change business models, organizational processes, digital infrastructures, and professional relationships (Leon, 2025; Mariani et. al, 2023). A rigorous analysis by authors study the role of artificial intelligence in innovation research through a systematic approach, showing that AI is predominantly treated as a cognitive infrastructure that supports innovation processes at the organizational, industrial and societal levels. The authors highlight the fact that AI is integrated into innovation not only as a technological tool, but as a factor that influences the way in which firms generate, evaluate and implement new ideas, including in contexts of digital transformation and structural change. AI appears associated with machine learning, big data and the Internet of Things, forming a technological core that allows the development of solutions with disruptive potential, through advanced automation, predictive analysis and strategic decision support (Mariani et al., 2023). The notion of "disruptive solutions" does not refer exclusively to the technical performance of algorithms, but to the ability of AI and ML to restructure existing ecosystems and generate new forms of value.

Specialized literature increasingly treats artificial intelligence (AI) and machine learning (ML) as technologies capable of generating structural transformations in multiple economic and social fields. The temporal analysis shows a sharp increase in interest in concepts such as “artificial intelligence”, “disruptive innovation”, “automation” and “business model innovation” since 2018, suggesting the consolidation of AI as a central element in studies of emerging and disruptive technologies.

The results of AI adoption include transformations in organizational performance, business models, innovation processes and competitive capabilities, indicating that AI facilitates the emergence of solutions that can change existing balances in markets and industries. AI and ML allow firms to move from incremental innovation to forms of innovation that affect market structures, customer relationships and industrial ecosystems (Mariani et. al, 2023).

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A distinct line of research concerns the distribution of intelligence and overcoming the centralized paradigm of data processing. Studies on federated learning and edge AI highlight that moving training and inference closer to the data source reduces latency, limits the transfer of sensitive data, and increases the scalability of intelligent systems (Letaief, 2022; Yang et al., 2025). When we think about advanced wireless networks and future 6G infrastructure, AI is no longer treated as an add-on application, but as a native network functionality, integrated into distributed architectures that combine communication, computing, and machine learning. This paradigm shift indicates that disruption occurs at the intersection of ML, infrastructure, and system design, not just at the algorithmic level.

In addition to the technological dimension, literature is paying increasing attention to the trust, risk, and responsibility associated with AI use. Studies on uncertainty quantification show that ML-based solutions must be evaluated not only by accuracy but also by calibration, transparency, and the ability to manage uncertainty in critical contexts (Deuschel, 2024). Uncertainty Quantification (UQ) is argued as a practical mechanism to make visible the limits and degree of confidence of predictions, especially in areas such as health, finance or autonomous systems (Deuschel, 2024). The authors propose a structuring of UQ methods depending on the moment of application (e.g. data-driven approaches, architecture changes, post-hoc) and discuss the evaluation of calibration through tools such as reliability diagrams and dedicated metrics (e.g. NLL, ECE), emphasizing that some metrics may favor more accurate models even if they are overconfident (Deuschel, 2024). This perspective is complemented by risk-based approaches, which treat AI simultaneously as a transformative factor and a source of systemic vulnerability, particularly in contexts related to cybersecurity, critical infrastructure, or the use of generative AI (Ahmed, 2025; Coman, 2024). Technical literature highlights the role of the interaction between algorithms and infrastructure in generating AI solutions with disruptive impact. In the field of autonomous vehicles, ML is integrated into the perception-planning-control chain, and reinforcement learning is used to manage sequential decisions in dynamic environments. Authors propose a pipeline that combines safe training with interpretable policy extraction, showing that safety and interpretability can be addressed simultaneously in autonomous systems (Plinge, 2024). At the same time, the literature indicates a shift in inference and training towards edge devices, where energy and memory constraints influence the design of ML solutions (Witt et. al, 2024). Federated machine learning is presented as a mechanism that changes the traditional centralized learning paradigm, reducing the risks associated with data privacy and network congestion (Yang et. al, 2025). The applicability of disruptive solutions based on AI and ML is illustrated in a variety of fields. In cybersecurity, ML and ensemble learning models enable the transition from reactive defensive mechanisms to adaptive systems capable of detecting unknown threats, including zero-day attacks (Schmitt, 2023). Likewise, scholars talk about investment, so understanding the factors that influence investment interest is a critical area of inquiry in both financial research and practice (Rad et. al, 2025), linked with AI. Consequently, recent multidisciplinary research highlights the need to include psychosocial, emotional, and socioeconomic factors in the analysis of behavioural intentions about sustainability, consumerism, and health, as well as other areas (Dicu et. al, 2025). We can add using modern technologies, such as AI, in this. For example, many start-ups have starting using AI quite extensively, but just as pilot projects, to test the efficiency of modern technologies (Lakatos et. al, 2026), equally important at the same time to understand communication techniques and strategies actively employed during interactions (Goian et. al, 2025), broadening the field of communication, including most importantly, digital communication

In IoT and industrial ecosystems, distributed ML supports real-time monitoring, control, and optimization of processes, contributing to the increased resilience of complex systems. In highly regulated professional fields (accounting or radiation protection), literature suggests that AI produces gradual rather than radical transformations. Studies show that generative AI and ML can support activities such as data analysis, report generation, or decision optimization, but their impact is conditioned by human expertise, data quality, and the ethical and institutional framework (Andresz, 2022; Bratianu & Lefter, 2001; Dumitrașcu, 2024). Examples indicate that the disruptiveness of AI depends on the context and the degree of maturity of the field in which it is implemented.

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Methodology

The method implemented consists of secondary data sourcing with descriptive synthesis. This means collecting and using existing data and it is the process of summarizing and integrating findings from those sources to describe patterns, trends, themes, or relationships. It focuses on explaining what the literature shows rather than calculating new numerical results and it implies studying the recent literature and how it reacts in time to different changes in society or in the world.

Results and discussions

During the analysis, some primordial applications or rather systems were used and focused mainly on research, such as:

AI-Scientist-v2
An advanced autonomous research system designed to generate complete scientific papers with minimal human input. It reportedly improves earlier versions by refining hypothesis generation, experiment design, and paper writing, and has been associated with workshop-level academic submissions (e.g., International Conference on Learning Representations or ICLR workshops).

Initial-AI-Scientist-pipeline
An earlier prototype framework for automated research that could take from certain databases a topic or idea, survey literature, design experiments (often simulated), and produce a full draft paper. It demonstrated the feasibility of end-to-end machine-driven research workflows.

AI-Cosmologist
An agent-based research system focused on scientific discovery tasks, particularly in theoretical or computational domains. It coordinates multiple specialized AI agents (for literature review, reasoning, coding, analysis) to basically collaboratively produce full research manuscripts. It is useful for quick generation of scholarly data, through compiling scientific evidence into a singular body of scientific text.

Project-Rachel
Consists in a large-scale experimental initiative aimed at generating multiple academic-

style outputs using AI. It explores scalability, showing that automated systems can produce numerous research drafts, reports, or papers in sequence, highlighting both productivity potential and quality-control challenges.

Regarding the AI usage in science, analyses of millions of scientific papers suggest 10–40 % of recent publications contain text likely generated or heavily influenced by AI tools like large language models depending on the field and detection method used (Modern Sciences.org, 16th July 2025). In biomedical abstracts, patterns in vocabulary suggest at least 13.5 % of 2024 papers were written with AI assistance. (Modern Sciences.org, 16th July 2025). Growth in AI used for scientific writing accelerated sharply after the release of ChatGPT in late 2022, marking a clear inflection point in adoption curves across fields (Modern Sciences.org, 22 August 2025). The issue of transparency is argued, such as disclosing the AI tool and how it was used is critical to uphold research integrity (Goyanes et. al, 2025). The key role of addressing these issues is using preventive tools to use AI in a productive and not counterproductive way.

We used a popular platform, named SemRush, which is a comprehensive, SaaS-based (Software as a Service) digital marketing platform designed for SEO (Search Engine Optimization), PPC (Points per click), content marketing, and competitive intelligence. It enables users to perform keyword research, audit website health, track keyword positions, and analyze competitor strategies. Used by over 10 million marketers, it is a leading tool for improving online visibility and optimizing search performance (according to SemRush.com). At the same time, SEMrush represents a prominent tool for competitive intelligence, providing a wide range of capabilities specifically tailored for market research (Kawuryan et. al, 2024). We have conducted a search for the count of results regarding identifying the frequency of a certain word on the Internet, first in Romania, then in other countries and finally, globally. In this context, Rogers' Diffusion of Innovations theory is particularly relevant, since cross-national differences in attitudes toward AI adoption are reflected in distinct adoption trajectories and information-seeking patterns. It was surprising to find that searching specifically on the first half of February 2026, with a slight increase daily, we notice approximately 301,000 searches of the keyword ChatGPT in Romania. On the other hand, in the United States, same search, indicated approximately 45.5 million searches of ChatGPT keyword, which is not at all surprising, considering the popularity of this platform. At the same time, we are excluding the ChatGPT application for Android or iOS for example, which has, again, a multitude of downloads. Rather than representing simple popularity differences, these variations suggest structural asymmetries in digital adoption and choice, technological awareness, and research-related information seeking/searching. Such disparities support the interpretation that the diffusion of AI tools follows a stratified global pattern consistent with innovation-diffusion theory, rather than a uniform adoption trajectory. This pattern indicates that online search intensity can function as a proxy indicator for early-stage technological adoption and epistemic interest within scientific and academic communities.

Temporal fluctuations in search patterns may provide insight into stages of technological diffusion, capturing transitions from initial awareness to evaluation and ultimately adoption. In this sense, search analytics can pose as an early diagnostic indicator of emerging epistemic trends, revealing how scientific communities respond to disruptive innovations before such responses become visible through publication outputs, citation patterns, or institutional implementation. This ultimately reinforces the methodological value of search data as a complementary empirical source for studying the global diffusion of artificial intelligence technologies.

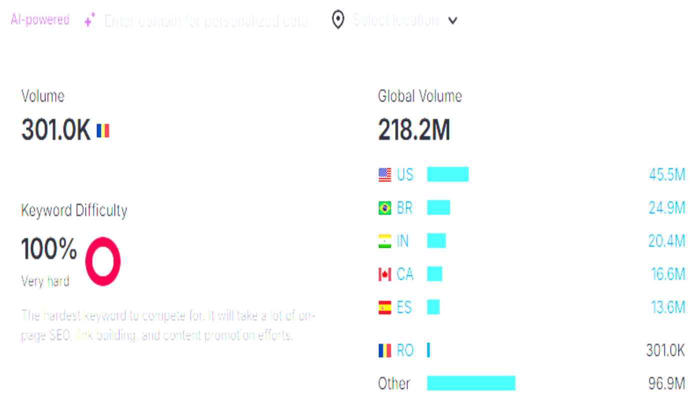

Figure 1. „ChatGPT" keyword search in the first half of February 2026
(Note: SemRush application for searching keywords and various domains)

As we can see, the count is high in various places in the world. In Brazil, for example, there are 24.5 million searches, in India 20.4 million, which is surprising, considering how much bigger India is in terms of population than Brazil, 16.6 million in Canada and 13.6 million in Spain. Globally, however, the volume reaches 218.2 million searches. The keyword difficulty is 100%, and it implies how difficult it would be for a website to rank organically in the Google top 10 for an analyzed keyword. The higher the percentage, the harder it will be to achieve high rankings. The CPC is set at 0.17$, which is the average price in dollars advertisers pay for a user's click on an ad triggered by an analyzed keyword (Google Ads). The intent is Navigational, which is the purpose of a search in a search engine, intents can be read by the search engine algorithms to show the proper results and SERP (Search Engine Results Page) features.

Other countries, after those highlighted above, form a total number of 96.9 million searches of the keyword ChatGPT. Regarding the competitive density, which is the level of competition between advertisers bidding on an analyzed keyword within their PPC campaigns. Competitive density is shown on a scale from 0 to 1.00 with 1.00 being the most difficult to rank for. ChatGPT searches for a satisfactory 0.08 Competitive density.

The „artificial intelligence" keywords are quite low, with only 2.900 in Romania, 95% keyword difficulty, and with the most being in India, 301.000, followed by the United States with 135.000, Indonesia, 33.100, as well as Philippines and the United Kingdom, sharing the same numbers. Globally, the number is 950.800. The competitive density this time is 0.29. The intent is not Navigational, like earlier, but this time Informational, the user wants to find a specific answer for a specific question. The total volume of 22.200 globally, contains searching for „agent in artificial intelligence" (80% keyword difficulty), „mathematics for artificial intelligence" (38% keyword difficulty), „artificial intelligence football predictor" (55% keyword difficulty) and „what is artificial intelligence" (80% keyword difficulty), followed by other 2.079 keywords related to artificial intelligence.

Google Gemini has been searched only 590 times in Romania, globally 34.3 million times, with almost all the searches (30.4 million), coming from India, followed by the United States with only 1.8 million, and then Mexico 550.000, Brazil 246.000 and the UK, 246.000. Globally, other countries than those mentioned, have 987.700 searches for Google Gemini. The keyword difficulty is 97%, no competitive density, which is 0, and a CPC of 0.15$. In terms of AI usage, while AI has the potential to enhance scientific productivity and clarity, its use raises ethical concerns regarding authorship attribution, bias, and transparency;

researchers and publishers emphasize the need for explicit disclosure of AI contributions in manuscripts (Goyanes et. al, 2025). From a theoretical perspective, these findings are consistent with diffusion-based models of technological adoption, according to which innovations spread unevenly across social systems depending on institutional, cultural, and infrastructural conditions (Kawuryan et. al, 2024). Thus, search volume data can be interpreted not simply as indicators of online interest, but as measurable signals of early-stage adoption and knowledge-seeking behavior in relation to emerging technologies. This can lead to better understanding of user behavior towards AI tools and better strategies to enhance knowledge-seeking without putting other entities at risk, such as scientific journals or simply by choosing relevant knowledge, such as personalized knowledge in an ethical manner.

Future research

The future might be, and could be taken into consideration, that directly refers to Agentic Tree Search, which is a strategy used in advanced AI systems where an autonomous agent plans, explores, and evaluates many possible action paths in a tree-like structure, instead of generating a single response or taking a single action.
It combines ideas from:

Tree search (like minimax or Monte Carlo Tree Search);

Autonomous agents (systems that can plan, act, observe, and revise certain aspects);

Large Language Models or AI planners that can reason, write extensive codes, run different kinds of tools, and reflect on outcomes beforehand.

This Agentic Tree Search should further be studied, analyzed and consolidated, as well as new means of using AI in an ethical manner. The main limitation consists in the inability to precisely control the way and pace in which users search for different AI venues, including answers to questions, fixes, AI companions, among others.

Conclusion

AI functions as a double-edged sword or transformative force in contemporary society, and it is not the tip of the issue just yet. On one edge, it amplifies and enhances productivity to a very large extent, accelerates discovery, and enhances decision-making across virtually all domains, increasingly outperforming traditional methods as technological maturity advances. On the other, excessive reliance on AI risks diminishing originality, individual reasoning, and authentic intellectual expression, potentially standardizing thought and narrowing cognitive diversity.

In the digital era, AI's true disruptiveness lies not only in automation but in its capacity to redefine systems, professions, and knowledge creation itself. It reshapes how problems are framed, solutions are generated, and value is produced, positioning AI as both an unprecedented enabler of progress and a structural force that challenges existing epistemic, economic, and social paradigms. As such, not only scientific use of AI is a potential threat, but also replacing human jobs such as clerks, public officers, even guides and, etc. The main issue lies within the risk of personal or unique knowledge estrangement, by using modern tools and technologies to perform simple or more difficult tasks for everyone based on their needs at that moment or overall. AI can certainly pose problems for creativity along users as it critically affects the capacity for creative thinking among people. There is a possibility where people will use AI so extensively that it will become a smokescreen between individual/creative thinking linked with subjectivity, and only using AI extensively even for the easier tasks in life. This is an issue as people will most likely ask for a second opinion from AI whenever they are in difficulty or have problems regarding even the simplest subject. At the beginning of AI, mainly the „ice-breaking" AI in 2022, with ChatGPT, going from simple advanced „dictionary" use, to 2026 where it became a real productive assistant in daily life, the integration was almost invisible in every platform, where it started to appear and conduct activities „behind the scenes". At the same time, companies are using AI to strengthen their policies and actions and simplify their strategies with less cost and less human intervention. Still, AI is a problem when it comes to ethical use, as it is still in the gray area of the spectrum, it is useful and somewhat accepted but at the same time sometimes wrong and worse when using it at some points rather than not using it.

AI Declaration: I did not use AI in the present paper.

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