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THE DISRUPTIVE IMPACT OF GENERATIVE AI: A LITERATURE REVIEW

O IMPACTO DISRUPTIVO DA INTELIGÊNCIA ARTIFICIAL: UMA REVISÃO DE LITERATURA

Amanda Gonçalves Oliveira GUEDES[1]
e-mail: amandaamog@icloud.com

Vinicius Amorim SOBREIRO [2]
e-mail: sobreiro@unb.br

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[1] University of Brasília, Brasília – Federal District – Brazil. Department of Management, Campus Darcy Ribeiro. Institution.
[2] University of Brasília, Brasília – Federal District – Brazil. Department of Management, Campus Darcy Ribeiro. Institution.

ABSTRACT

Purpose: This study aims to present a literature review on the dark side of generative artificial intelligence (GenAI), drawing on previously published research. **Theoretical framework**: Research addressing common perspectives on the already identified impacts of GenAI on human activities is limited in recent literature. **Methodology/Approach**: The study applies the five-step method for identifying research gaps proposed by Jabbour (2013), Seuring (2013), and Lage Junior and Godinho Filho (2010). **Findings**: The results indicate a consensus in the literature regarding the impacts of GenAI. **Research, practical & social implications**: The study suggests a common perspective concerning the effects of GenAI on the labour market. **Originality/Value**: This study contributes by addressing the negative impacts of GenAI based on existing literature.
Keywords: Generative artificial intelligence. Dark side.

RESUMO

Objetivo: O objetivo deste estudo é apresentar uma revisão de literatura no tocante ao lado sombrio da GenAI a partir de estudos previamente publicados. **Referencial teórico**: A literatura mais recente carece de estudos sobre perspectivas comuns, dos impactos da GenAI, nas atividades realizadas pelos humanos, já identificados. **Metodologia/Abordagem**: O método dos cinco passos para identificação de gaps de Jabbour (2013), Seuring (2013) e Lage Junior & Godinho Filho (2010) foi utilizado. **Resultados**: Os resultados indicam que há um consenso na literatura sobre os impactos da GenAI. **Contribuições, implicações práticas e sociais**: O estudo indica que há um ponto comum sobre os efeitos da GenAI no mercado de trabalho. **Originalidade/Valor**: O valor do estudo está em abordar os impactos negativos da GenAI a partir da literatura existente.

Palavras-chave: Inteligência Artificial Generativa. Lado sombrio.

Introduction

Artificial intelligence (AI), and more specifically, generative artificial intelligence (GenAI), is currently one of the most prominent topics in business and academic environments (Barari, Casper Ferm, Quach, Thaichon, & Ngo, 2024, p. 1234). They evidently serve as facilitating tools in various areas of human knowledge. According to Ineli-Ciger (2024, p. 1), defining AI and its corollary, GenAI, is challenging because this concept encompasses several domains of human knowledge, such as computing, mathematics, neuroscience, and psychology, as perceived by Pereira, Hadjielias, Christofi, and Vrontis (2023, p. 1). However, in their studies on morality within this theme, Misselhorn (2018, p. 161) aptly notes that *artificial intelligence aims to model or simulate human cognitive abilities*.

Building on this definition within an economic context, the presence of these tools in product manufacturing processes—essentially in production processes—is widely accepted across various industrial sectors of modern economies (Pereira, Hadjielias, Christofi, & Vrontis, 2023, p. 1). However, what stands out today is the increasing presence of these tools in the service industry. Several factors may explain this growing prevalence. Recent studies, such as those by Casu, Guarnera, Caponnetto, and Battiato (2024, p. 6); Zhou, Yi, Rasiah, Zhao, and Mo (2024, p. 3); Hu and Min (2023, p. 1); and Grewal, Guha, Satornino, and Schweiger (2021, p. 230), describe the provision of efficient and personalised services to users as a key characteristic sustaining their importance, mimicking relationships that can occur in society. Broadly speaking, this entire process relies on GenAI's ability to generate new content, such as texts, images, and audio, in response to human requests. This ability is, in turn, due to GenAI's capacity to recognise patterns and learn from the data provided by users or consumers themselves (Casu, Guarnera, Caponnetto, & Battiato, 2024, p. 6). Because these systems learn from human-provided data, the solutions or responses presented by GenAI systems are, or may be, indistinguishable from content created by human beings. Thus, such tools are easily used as instruments for data manipulation, which raises concerns regarding privacy, manipulation, and data security (Hu & Min, 2023, p. 1; Chen et al., 2023, p. 12; and Grundner & Neuhofer, 2021, p. 3).

According to Grzybowski, Pawlikowska-Łagód, and Lambert (2024, p. 222), the evolution of computers and what is known today as AI has occurred gradually over more than two centuries, through a long series of stages. According to their study, the main periods or events that supported the development of this field of knowledge can be summarised as follows:

- The first computers: It is worth highlighting the work of mathematicians Charles Babbage (1791–1871), who created the first analytical machine or functional mechanical computer around 1822, and Alan Turing (1912–1954), who invented the "Turing Machine" in 1936 (Grzybowski, Pawlikowska-Łagód, & Lambert, 2024, p. 224). Many researchers, such as Davis (2011) in his book *The Universal Computer: The Road from Leibniz to Turing* and Copeland (2004) in his study *The Essential Turing*, consider Turing as the patron of modern computing, since many of his propositions form the current theoretical foundations of this field;
- The first AI programs: Around 1950, Christopher Strachey and Dietrich Prinz developed draughts and chess games, respectively. According to Grzybowski, Pawlikowska-Łagód, and Lambert (2024, p. 225), this marks an important milestone for the field, as both featured advanced logic for the time and were, more importantly, capable of running on personal or common computers. In an academic context, these researchers highlight two significant developments offering greater processing capacity. The "Logic Theorist" program, with logical reasoning capability, was developed by Allen Newell, J. C. Shaw, and Herbert A. Simon between 1955 and 1956. The Neocognitron was an algorithm proposed by electronic engineer Kunihiko Fukushima around 1979. These programs presented many of the fundamental concepts of artificial neural networks (ANN);
- Deep Blue: In the early 1990s, considerable effort was devoted to merging concepts from the natural sciences, such as biological concepts, with computing (Muthukrishnan et al., 2020, pp. 398–397). These advances provided an ideal environment for IBM to create Deep Blue to play chess by combining specific hardware and software derived from the Deep Thought project. According to Grzybowski, Pawlikowska-Łagód, and Lambert (2024, p. 226) and Dailey, Hair, and Watkins (2014, p. 169), Deep Blue was able to defeat the famous chess player and world champion Garry Kimovich Kasparov in 1997. At the time, this event highlighted the processing speed and intellectual superiority of the machine over humans;
- Natural language processing (NLP): With the advancement of neural networks and modern deep learning techniques in the 2010s, NLP began to achieve impressive results with its ability to process and understand language with much greater precision. In brief, NLP is a collection of computational techniques for the automatic analysis and representation of human languages (Chowdhary, 2020, p. 604). In the current context, Professor Chowdhary's (2020, p. 10) observation of AI and GenAI indicates that NLP is widely used in information retrieval, machine translation, question-answering chats, and summarization;
- T-NLG and its successors: Microsoft® introduced the Turing natural language

generation (T-NLG) around 2020 (Grzybowski, Pawlikowska-Łagód, & Lambert, 2024, p. 226). Broadly speaking, T-NLG is an NLP algorithm far superior to its predecessors. To illustrate this difference, at the time, T-NLG could employ 17 billion parameters, whereas its predecessors could utilise only 8.3 billion parameters. However, in 2020, OpenAI®, a company founded in 2015, developed ChatGPT-3, which, in turn, utilised 175 billion parameters and 96 training layers (Dale, 2020, p. 115; Dwivedi et al., 2023, p. 3). According to Dwivedi et al. (2023, p. 3), ChatGPT-3 was trained using information and data from various sources on the internet, such as web pages, books, research articles, and chat conversations. As a practical outcome, in 2022, ChatGPT-3 drew significant attention by providing robust answers to questions spanning vast areas of human knowledge. According to Grzybowski, Pawlikowska-Łagód, and Lambert (2024, p. 226), this 2023 event led to the publication of an editorial in the journal *Nature Biomedical Engineering* (N.B.E). Published by Springer Nature, this journal is part of the Nature Portfolio. According to the editorial:

> *it is no longer possible to accurately distinguish text written by a human mind from that generated by a highly parallelizable artificial neural network with substantially fewer neural connections.* (N.B.E., 2023, p. 85)

GenAI can rapidly process data in its natural form; hence, mining unstructured data such as raw text and images is already a reality in many applications (Dwivedi et al., 2023, p. 3). Software, platforms and/or websites, voice assistants, and Internet of Things (IoT) devices are some of these applications with significant impacts in various areas, such as:

- Administrative process automation (Malik & Froese, 2022, p. 683);
- Industrial automation and robotics (Grewal, Guha, Satornino, & Schweiger, 2021, p. 234; Fang, Han, & Chen, 2024, p. 8);
- Content creation, entertainment, and interactivity (Stokel-Walker & Van Noorden, 2023, p. 215);
- Law (Ineli-Ciger, 2024, p. 3);
- Education and training (Playfoot, Quigley, & Thomas, 2024, p. 1; Else, 2023, p. 423);
- Economics, finance, and accounting (Gedikli, Sharma, Erdoğan, & Hammoudeh, 2024, p. 1; Malik & Froese, 2022, p. 683);

- Marketing, sales, and customer support (Fang, Han, & Chen, 2024, p. 1; Scarpi, 2024, p. 1; Grewal, Guha, Satornino, & Schweiger, 2021, p. 229);
- Healthcare and medicine (Ali, et al., 2023, p. 6);
- Public safety (Dubravova, Cap, Holubova, & Hribnak, 2024, p. 237).

Consequently, AI and, specifically, GenAIs have already found their place in everyday life. According to Grewal, Guha, Satornino, and Schweiger (2021, p. 229) and Tussyadiah and Miller (2019, p. 359), despite the growing trend of using GenAIs and the numerous literature reviews, such as those by Bolaños, Salatino, Osborne, and Motta (2024), Wang et al. (2024), Ali et al. (2023), Mariani, Machado, Magrelli, and Dwivedi (2023), Pereira, Hadjielias, Christofi, and Vrontis (2023), Wagner, Lukyanenko, and Paré (2021), Silva et al. (2020) and Ain, Vaia, DeLone, and Waheed (2019), a gap in the literature still exists in research focused on the negative aspects of GenAI. While GenAI offers numerous benefits, these technological advancements optimise operational efficiency and also usher in a wave of automation in areas traditionally dominated by human labour, as highlighted by Arias-Pérez and Vélez-Jaramillo (2021, p. 1481) and Frey and Osborne (2017, p. 255). This raises several research questions, such as:

- What are the primary short- and long-term GenAI advancements on society?
- To what extent should GenAI progress to maintain a harmonious relationship with society?
- What are the proposed solutions to address any negative impacts?
- Are GenAIs governed by any monitoring, control, or regulatory bodies?

Based on these questions, this article aims to present the key common points in the answers to these questions, as well as the existing gaps in the specialised literature regarding the negative impacts of GenAI advancement. For this purpose, the five-step method proposed by Jabbour (2013), Seuring (2013), and Lage Junior and Godinho Filho (2010) was employed. This involved relevant scientific articles in this field published on the Science Direct® or Scopus® platform by Elsevier®.

The remainder of this article is structured as follows: Section 2 explains the research method. Subsequently, Section 3 details the coding and classification process of the articles used. Section 4 presents the results obtained and the main arguments justifying these results.

Finally, Section 5 presents the main conclusions, as well as directions for future studies.

Method

A systematic review is characterised as a rigorous research method that encompasses the structured processes of identifying, critically appraising, synthesising, and analysing evidence from relevant studies within a specific domain (Liberati et al., 2009). Hence, to enhance the understanding of the emerging research problem, the authors employed a systematic approach based on the five-step method, widely validated in academic literature and employed in highly regarded journals such as Resources, Conservation and Recycling, Decision Support Systems, and the International Journal of Production Economics. Lage Junior and Godinho Filho (2010), Jabbour (2013), and Seuring (2013) define this method as the orderly and careful execution of the following steps:

- First step: Conduct a systematic search for research articles available in a database;
- Second step: Develop a simple classification and coding structure that facilitates the analysis of information and data granularity;
- Third step: Apply the developed classification structure to group and, specifically, to synthesise information;
- Fourth step: Identify the current composition of the *status quo* of knowledge provided by researchers in the addressed area, according to the developed coding and classification;
- Fifth step: Analyse and discuss the results to identify the established positions in the field and the existing gaps.

It is important to emphasise that the five-step method has been successfully applied in literature review processes addressing a wide range of subjects, as clearly demonstrated by Pinto and Sobreiro (2022, p. 4). They highlight its use in the studies by Lee et al. (2021), Henrique, Sobreiro, and Kimura (2019), Masudin and Fernanda (2019), Salim, Ab Rahman, and Abd Wahab (2019), Nazário, Silva, Sobreiro, and Kimura (2017), and Mariano, Sobreiro, and Rebelatto (2015). This illustrates the methodological robustness of the approach, as well as its versatility in different research contexts. Furthermore, Snyder (2019, p. 333) highlights that a literature review must address research questions with a depth that no single study can achieve and provide a broad view of diverse and interdisciplinary research areas.

Based on this context, the first stage of this research was conducted between August and September 2024. It involved a search using the keywords “Artificial Intelligence”, “GenAI”, “problems”, “Dark”, and “Dark Side”, utilising Boolean operators, considering the titles and abstracts of studies published between 2020 and 2025. We utilised the Science Direct® or Scopus® database published by Elsevier® for the search, since it is recognised as one of the most comprehensive and authoritative bibliographic databases worldwide and is commonly available at most universities. Given that this topic spans various areas of knowledge, the number of identified studies was significant. Consequently, to further delimit the study subject, we applied a filter of fields of knowledge to the search. In this case, we chose journals from the following fields for publishing the study:

- Business, management, and accounting;
- Social science.

After parametrisation and adjustment, 87 studies were identified in the database. These studies were screened by carefully reading all the abstracts to exclude those containing the previously indicated keywords, such as those by Das, Dutta, and Tsapakis (2020) and Großmann, Merfeld, Klein, Föller, and Henkel (2024), without a direct and explicit relationship with the theme of this research. Consequently, from the 87 articles, we identified 28 articles that were aligned with the theme. Brief summaries of each of these articles are presented in Table 1.

Table 1

Brief summaries of selected articles

Studies	Brief summary
Bamel, Kumar, Lim, Bamel, & Meyer (2022).	The research seeks to examine the impact of digitalisation on the workplace, considering the context of COVID-19 and the human resource practices that assist in this process.
Barman, Guo, & Conlan (2024).	The research analyses the impact of disinformation generated by large computational natural language processing models, such as ChatGPT®.
Breidbach (2024).	The research aims to present guidance to managers and policymakers regarding decision-making based on artificial intelligence algorithms and how to implement this technology responsibly.
Buck, Clarke, Torres de Oliveira, Desouza, & Maroufkhani (2023).	The research seeks to present the effects of digital transformation on the business environment and society. Additionally, the authors highlight gaps for studies in the business context of asset-concentrated organisations.
Cao, Duan, Edwards, & Dwivedi (2021).	The research highlights the importance of creating favourable conditions, addressing personal concerns of managers, and balancing the benefits and risks of AI in decision-making.
Cao, Chen, Dong, Wang, & Qin (2023).	The research seeks to show that AI can generate or present unethical behaviours.
Conca (2023).	The research aims to present how Virtual Assistants (VAs) are on the rise and how such tools can generate deceptive designs with the objective of influencing users' decision-making.
Dabić, Maley, Švarc, & Poček (2023).	The research presents how digitalisation has changed the work environment, contextualising polarisation, out-of-standard situations, and work on digital platforms. It is important to note that this process is carried out considering two approaches, namely: i) dystopian; and ii) utopian.
Edna Ozuna (2024).	The research analyses the interaction between hosts and guests through service robots, highlighting economic aspects and asset management.
Ehsan & Riedl (2024).	The research presents and discusses the harmful effects in the process of adjusting the reliability of AI models.
Gaczek, Leszczyǹski, & Mouakher (2023).	The research seeks to analyse the relationship between negative emotions and collaboration with AI in the context of Customer Relationship Management (CRM).
Gligor, Pillai, & Golgeci (2021).	The research seeks to analyse how new technologies, such as AI, blockchain, and big data, can generate dark side effects in the context of business-to-business (B2B) relationship management.
Grewal, Guha, Satornino, & Schweiger (2021).	The research explores the positive and negative impacts of AI on the business-to-consumer (B2C) and business-to-business (B2B) environments.
Grundner & Neuhofer (2021).	The research analyses the impacts of AI on service ecosystems focused on tourism.
Hu & Min (2023).	The research presents a discussion relating to the "eye of the observer effect" and AI in service delivery.
Kraus, Ferraris, & Bertello (2023).	The research presents the role of AI as an agent in business-to-business (B2B) networks and, consequently, the occurrence of dehumanisation problems.
Kraus, Ferraris, & Bertello (2023).	The research presents a literature review on the impacts of AI on the job market.
Malik & Froese (2022).	The research presents the idea of "perverse innovation", that is, the impact of digitalisation on corruption from the perspective of the "moral intensity" theory.
Marsh, Vallejos, & Spence (2022).	The research presents a discussion about the increase in digital work due to COVID-19, considering the benefits and negative aspects of digital technologies.
Mostafa, Lages, & Shaalan (2024).	The research presents an investigation into the use of Virtual Agents (VAs) in the business environment in the role of customer service.
Pan, Lin, & Wong (2025).	The research analyses how to balance technological innovations with

	employee well-being. In this context, the authors indicate that excessive automation can influence humanistic skills.
Papagiannidis, Mikalef, Conboy, & Van de Wetering (2023).	The research presents the negative aspects of AI adoption in a business context based on the case of a Norwegian company in the electric energy sector.
Satornino, Grewal, Guha, Schweiger, & Goodstein (2023).	The research presents a discussion about the use of AI in technology-based peer-to-peer (P2P) markets.
Scholze & Hecker (2024).	The research presents the positive and negative impacts of the digitalisation process on employee well-being and the work environment.
Shepherd & Majchrzak (2022).	The research examines the long-term societal implications of AI. Additionally, the authors address how the combination of AI with entrepreneurship techniques can create what they call “super tools”.
Zhou, Wang, & Chen (2023).	The research seeks to present the negative effects of AI in the area of Human Resource Management (HRM).
Zhou, Yi, Rasiah, Zhao, & Mo (2024).	The research presents how AI has impacted employee behaviour and emotions based on information from 92 individuals.
Zhu, Huang, Lu, Luo, & Zhu (2024).	The research presents the impacts of AI on gig economies, that is, in service provision.

After selecting the articles, as indicated by Pinto and Sobreiro (2022, p. 5), Jabbour (2013, p. 145), and Lage Junior and Godinho Filho (2010, p. 14), we executed the second step of the method, in which the articles were classified into categories of analysis using distinction codes. Based on this classification and the third step of the method, we summarised the available scientific knowledge to provide a broader view of the study area. To this end, a database was developed using the SQLite library of the C programming language, utilising the open-source application DB Browser for SQLite. Consequently, after inserting all the data from the articles into this database, scripts were developed following the practices and conventions of the SQLite library. These scripts were used for generating “triggers” and “views” capable of encompassing and automating steps four and five of the method. In this context, the next section will present the main points observed concerning the classification and coding developed to identify the results obtained.

Classification and coding

Based on the previously identified articles, a set of characteristics was established through coding to categorise the articles into groups. Specifically, these articles were categorised based on classifications and sub-classifications relevant to the theme of the current study. Similar to the study by Pinto and Sobreiro (2022, p. 8), this set of characteristics is composed of nine classifications, numbered from 1 to 9. These were subsequently combined with sub-classifications represented by letters. The structure with all classifications, sub-classifications, and codes is presented in Table 2. For example, the code 1D indicates that the article belongs to sub-classification D regarding classification 1. Furthermore, it must be noted that an article may be classified into more than one sub-category.

Table 2

Classification and coding framework

Classification	Meaning	Codes
1	Context	1A - Marketing. 1B - Finances, business and market. 1C - People management. 1D - Ethical and legal. 1E - Services. 1F - Does not apply.
2	Social impact	2A - Job losses. 2B - Decreased social relations. 2C - Unverified learning. 2D - Decision-making. 2E - Disinformation/Fake News. 2F - Does not apply.
3	Social manipulation	3A - Economy (Consumption). 3B - Politics (Election). 3C - Scientific (Disinformation). 3D - Does not apply.
4	Beneficiaries	4A - Companies. 4B - Government (Politics). 4C - Persons. 4D - Does not apply.
5	GenAI applications	5A - ChatBot and virtual assistent. 5B - Voice assistent. 5C - Text-to-image model. 5D - Text-to-video model. 5E - Text-to-audio model. 5F - Service robots. 5G - More than one technology. 5H - Does not apply.
6	Method	6A - Quantitative. 6B - Qualitative. 6C - Qualitative and quantitative. 6D - Survey. 6E - Literature review. 6F - Case study. 6G - Does not apply.
7	Economic context.	7A - Developed countries. 7B - Developing countries. 7C - Not mentioned. 7D - Does not apply.
8	Geographical region.	8A - Africa. 8B - America. 8C - Oceania.
9	Data security	9A - Mentions. 9B - Not mentioned.

	9C - Data leaks. 9D - Lack of trust. 9E - Data manipulation. 9F - Does not apply.

Classification 1 addresses the context of the research, which is the area in which the research was conducted. The scale of sub-classifications ranges from A to F. These areas were chosen based on the discussions presented in the following studies:

- Mostafa, Lages, and Shaalan (2024, p. 1): Marketing;
- Grewal, Guha, Satornino, and Schweiger (2021, p. 229): Finance and business;
- Dabić, Maley, Švarc, and Poček (2023, p. 1): People management;
- Malik and Froese (2022, p. 682): Ethical and legal studies;
- Edna Ozuna (Edna Ozuna, 2024, p. 1): Services.

Based on these five areas, this categorisation aims to highlight the areas where the negative or positive impacts are more evident. It must be noted that many other areas could have been considered in this classification, but we opted for this set because all the scientific articles should belong to the fields of Business, Management and Accounting, or Social Science in the Science Direct® database, as previously stated. Furthermore, in this classification, as well as in the others, a sub-classification "Not applicable" was included to cover situations in which the articles did not belong to any of the previously presented categories.

Classification 2, structured on the coding scale A–F, aims to identify the social impact caused by the rapid advancement and use of GenAI on society. For this assessment, we created sub-classifications that could indicate such impacts. In this regard, sub-category "2A", named "Reduction of jobs", was established based on the studies by Frey and Osborne (2017, p. 286), Arias-Pérez and Vélez-Jaramillo (2021, p. 1476), and Dabić, Maley, Švarc, and Poček (2023, p. 3). We also established sub-classifications "2B", "2C", "2D", and "2E" to identify the impacts of AI on relationships between individuals, the learning process in the interaction between AIs and humans, decision-making processes, and the generation of misinformation or fake news, respectively.

Similarly, Classification 3 presents a coding structure composed of sub-classifications from "A" to "D", which indicate the sector in which social manipulation occurs. It is expected that the sub-category "3A – Economy", related to consumption, will be the most cited, as it covers many topics. We also established two more sub-categories, "3B" and "3C", which encompass the areas of politics and science, respectively, given that AIs and GenAIs can be used in these contexts.

Continuing the idea of Classification 3, Classification 4 seeks to identify the beneficiaries of social manipulation resulting from the rapid use of AIs and GenAIs. The classification is structured from A to D. Particularly, the sub-category “4A – Companies”, which currently use AIs and GenAIs as facilitators and profit drivers in their businesses, is expected to be predominant (Zhou, Yi, Rasiah, Zhao, & Mo, 2024, p. 1). Studies such as those by Scholze and Hecker (2024, p. 1) and Zhou, Wang, and Chen (2023, p. 1222) were considered in the sub-category “4D – Not applicable”, as these studies do not directly indicate their beneficiaries.

Among the various AI and GenAI applications currently in operation and freely accessible to users, Classification 5, coded from A to H, seeks to identify which application is likely to have the most significant and detrimental impact on society. Similar to the study by Pinto and Sobreiro (2022, p. 8), Classification 6, structured on the coding scale A–F, indicates the research method used by the authors in developing their research on the dark side of GenAI. This classification aims to identify the most common methods used to address the topic and to identify trends in research.

Similar to the studies by Jabbour (2013, p. 145) and Pinto and Sobreiro (2022, p. 8), Classification 7 aims to identify the economic context in which the articles are situated, considering the countries from which the research data for this study were obtained. The coding was done using the letters A–D. It must be noted that developed countries tend to have easier access to these technologies. Thus, this category relates the economic perspectives of the regions with concerns about AIs and GenAIs, which are evident in an academic context (Bamel, Kumar, Lim, Bamel, & Meyer, 2022, p. 1).

In parallel with the previous classification, Classification 8 aims to identify the geographical region of the research by indicating the continents related to the article data in the database. By combining the information from Classification 7 with Classification 8, we can identify whether any geographical region predominates over others, given that studies conducted in different locations may present particular characteristics due to various factors, such as cultural, economic, or religious. Finally, Classification 9 refers to data security, coded from A to F. Based on the study by Breidbach (2024), this topic has been frequently addressed in recent academic studies on AI, GenAI, and digitalisation.

Results and discussion

Based on the framework presented in Table 2, the 28 articles were classified to identify common traits regarding each previously established category, as presented in Table 3. We sought to establish the consensus and the existing gaps concerning the dark side of GenAI from the perspective of each category, as presented below.

Table 3

Brief summaries of the selected articles

Results of classifications								
1C	2A	3A	4D	5G	6E, 6F	7C	8G	9A
1D	2E	3B, 3C	4B	5G	6B	7C	8G	9C
1B, 1D	2D	3A	4A	5G	6B	7C	8G	9C, 9E
1B	2F	3A	4A	5A	6B, 6D	7A	8C	9A
1B	2A	3A	4D	5G	6B, 6D	7A	8D	9B
1D	2B	3A	4A	5G	6D	7A	8B	9B
1D	2D	3A	4A	5A	6B	7A	8D	9E
1C	2A	3A	4A	5A	6E	7A	8F	9B
1E	2B	3D	4D	5G	6E	7A	8B	9F
1E	2C	3D	4D	5G	6F	7C	8G	9E
1A	2A	3A	4A	5G	6D	7A	8G	9A
1B	2B	3A	4A	5G	6B	7C	8G	9B
1A, 1B	2A	3A	4A	5G	6B	7A	8F	9D
1B	2A, 2B	3A	4D	5G	6E	7C	8G	9A
1D, 1E	2F	3A	4D	5G	6E	7C	8G	9C

Continues on the next page.

Results of classifications								
1A	2A, 2B	3A	4A	5G	6B, 6E	7C	8G	9A
1B	2F	3A	4D	5G	6G	7C	8G	9A
1B, 1D	2F	3A	4A, 4C	5A	6E	7A	8F	9C
1C	2B	3A	4A	5A	6E	7C	8G	9A
1A	2B	3D	4A	5A	6D	7A, 7B	8A, 8E	9F
1E	2A, 2B	3A	4A	5F	6D	7A	8E	9F
1B	2A	3A	4D	5G	6D, 6F	7A	8D	9A
1B	2D	3A	4A	5A	6B	7C	8G	9D, 9E
1B, 1C	2B	3A	4D	5A	6A, 6D	7C	8G	9A
1B	2C	3A	4A	5G	6B	7D	8H	9A
1C	2B	3A	4D	5G	6E	7C	8G	9C, 9D
1E	2A	3A	4D	5F	6D, 6A	7A	8E	9F
1B	2D	3A	4A	5G	6D	7A	8E	9A

Select papers
Bamel et al. (2022).
Barman et al. (2024).
Breidbach (2024).
Buck et al. (2023).
Cao et al. (2021).
Cao et al. (2023).
Conca (2023).
Dabić et al. (2023).
Edna Ozuna (2024).
Ehsan and Riedl (2024).
Gaczek et al. (2023).
Gligor et al. (2021).
Grewal et al. (2021).
Grundner and Neuhofer (2021).
Hu and Min (2023).

Select papers	Keegan et al. (2023).	Kraus et al. (2023).	Malik and Froese (2022).	Marsh et al. (2022).	Mostafa et al. (2024).	Pan et al. (2025).	Papagiannidis et al. (2023).	Satornino et al. (2023).	Scholze and Hecker (2024).	Shepherd and Majchrzak (2022).	Zhou et al. (2023).	Zhou et al. (2024).	Zhu et al. (2024).

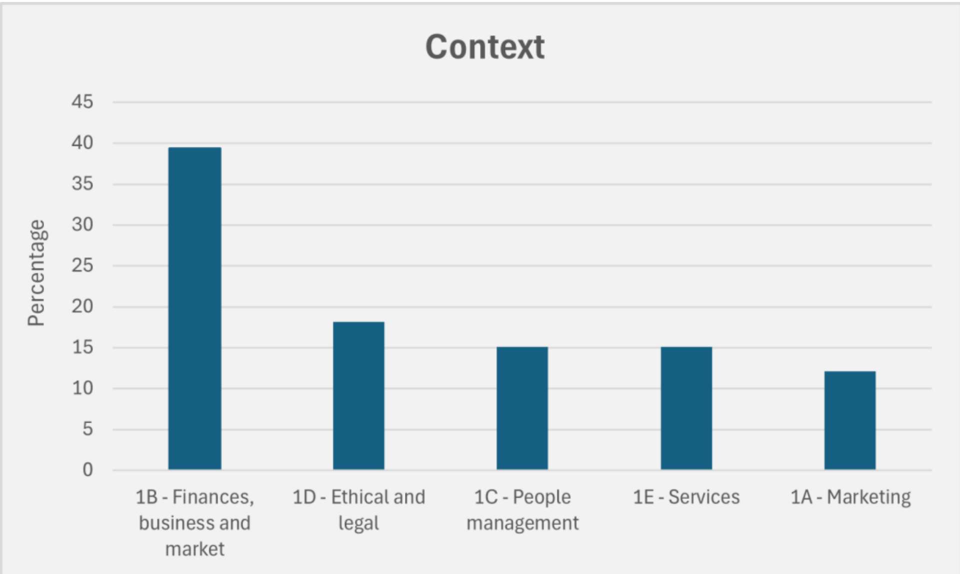
Context

The category "Context" focuses on the various areas in which AI is embedded, mainly emphasising the applied social sciences to better concentrate studies. Understanding areas with higher concentrations of studies helps identify the common points and research gaps on the topic and determine the areas that future studies must focus on.

In this category, a higher frequency was observed in the coding of "1B – Finances, business and market", as shown in Figure 1. This sub-category accounted for approximately 39% of the analysed articles, whereas a lower volume of research was observed in the other categories, and no research was classified in category 1F.

Figure 1

Context



Notes. 1A – Marketing, 1B – Finances, business and market, 1C – People management, 1D – Ethical and legal, 1E – Services, and 1F – Does not apply.

These results demonstrate that the majority of research is concentrated in the area of finance, business and market. A likely explanation for this finding could lie in the digitalisation of these areas, as there is much room for the implementation of GenAI, as pointed out by Bamel, Kumar, Lim, Bamel, and Meyer (2022) and Kraus, Ferraris, and Bertello (2023). The results also indicate that the digitalisation process has a strong impact on the costs of these operations. On another note, we identified a lower volume of studies in the marketing context, which, in turn, helped identify the following gaps:

- G1*: Are GenAIs ineffective in the digitalisation process in marketing?*
- G2: *Is the creativity of GenAIs insufficient to innovate significantly to capture consumer attention with minimal input or without the supervision of a professional in the field, since their services equal those commonly available in the sector?*

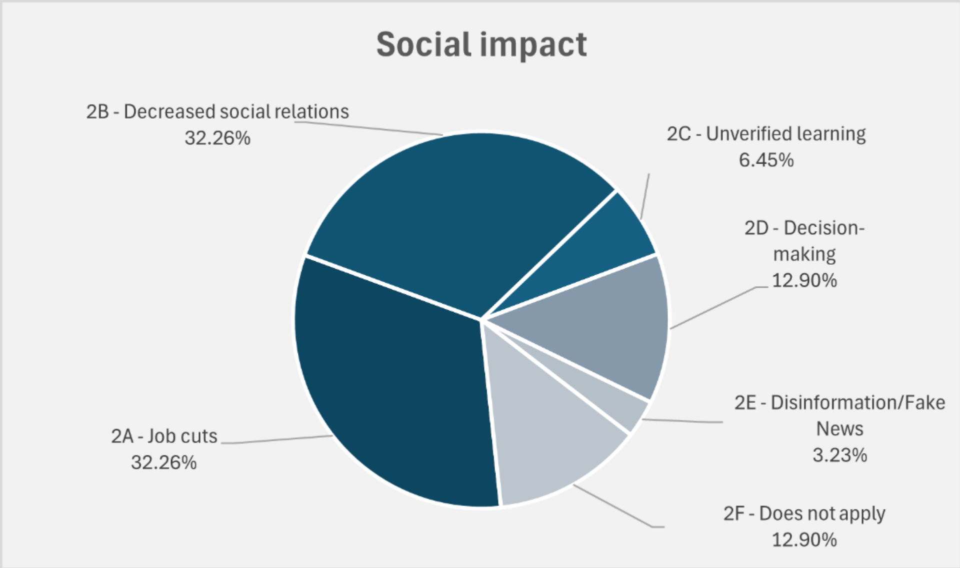
To illustrate G2, we note the several currently available GenAI services for professionals in soundtrack production for commercials. Thus, today, these GenAIs are efficient in creating just a piece or part, such as a vocal for the soundtrack, but they still do not produce impressive results when requested to create an entire soundtrack.

Social impact

Based on data from the International Labour Organization (ILO) published since 2018, Dabić, Maley, Švarc, and Poček (2023) state that the impact of digitalisation will be extremely significant. From this point onwards, we attempted to measure how the literature addresses this and other social impacts generated by GenAI. Consequently, we identified heightened concerns with "2A – Reduction of jobs" as well as "2B – Decrease in social relationships", as both were identified in 32% of the studies, as shown in Figure 2.

Figure 2

Social impact



Notes. 2A – Job cuts, 2B – Decreased social relations, 2C – Unverified learning, 2D – Decision-making, 2E – Disinformation/Fake News, 2F – Does not apply.

This high rate is supported by many studies, which emphasise the importance of greater attention to the future of jobs, as highlighted by Scholze and Hecker (2024, p. 1). Linked to this concept, social relationships may decrease precisely in the professional sphere, as GenAI advances in B2B and B2C spaces. The classification "2D – Decision-making" has a small share of appearances, accounting for only about 13% of the category, illustrating a low volume of studies regarding the impact of GenAI on the decision-making of companies and consumers. On the other hand, few studies focused on verifying the information generated by GenAI in providing simple clarification or in learning. As a consequence, the following gaps are identified:

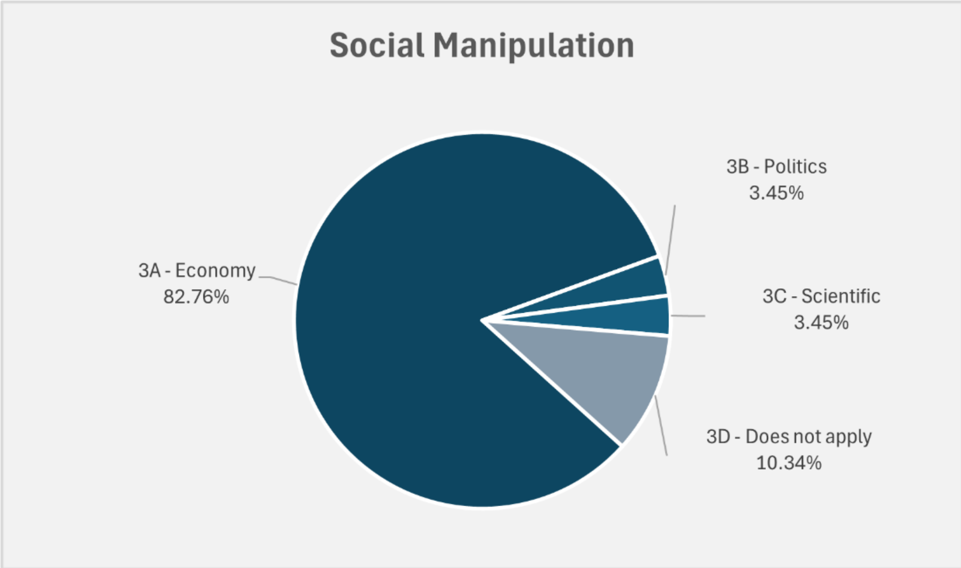
- G3: *Limited research is available on the negative side of GenAI-supported learning, given that the concepts are often not verifiable from the perspective of the teacher or the learner.*
- G4: *A research gap exists regarding "Disinformation, Fake News" and GenAI. It is important to highlight that the advancement of AI applications such as "Text-to-Image" or "Text-to-Video" has led to an increase in the misuse of these technologies, facilitating the dissemination of altered information or falsehoods by GenAI. This can subsequently be shared en masse with the help of AI applications.*

Social manipulation

Conca (2023, p. 1) defines a virtual assistant (VA) as software that allows users to operate smart devices through voice commands to build a long-term relationship with the user. Conca further elaborates that VAs were designed to encourage and influence users to interact with them regarding tasks such as making purchases, listening to news, playing music, and browsing web pages, by constantly sharing data with VAs. This is an example of a context in which GenAI can influence preferences, choices, and habits, indicating the scope of this study. Thus, the category “Social Manipulation” aims to identify the sectors in which this manipulation occurs, according to the previously considered studies. Consequently, we identified that the category “3A – Economy”, primarily associated with consumption, has a representation of 82%, as shown in Figure 3.

Figure 3

Social manipulation



Notes. 3A–Economy, 3B–Politics, 3C–Scientific and 3D–Does not apply.

Consequently, the category "3A" is most related to the dark side of GenAI, according to the studies considered. On the other hand, the sub-categories "3B – Political" and "3C – Scientific" indicated low representation in the studies considered. This subsequently generates G5, which is as follows:

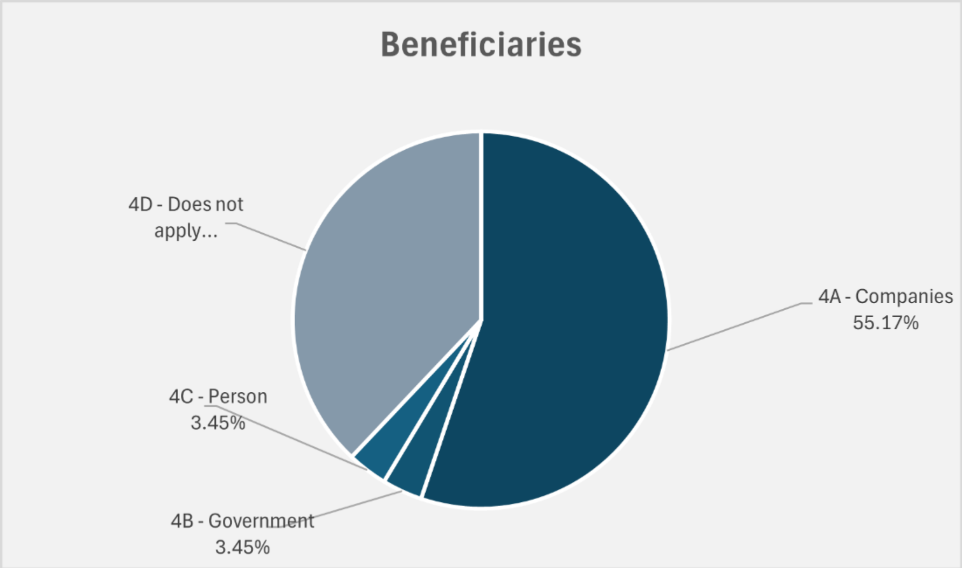
- G5: *Why is GenAI not yet used as a tool for social manipulation in politics?*

Beneficiaries

In line with the last classification, understanding the beneficiaries of social manipulation is highly relevant, as it reveals the main funders of these technologies, as well as those behind this manipulation, to the consumers of GenAI. As expected, the coding "4A–Companies" accounted for 55% of the classified articles, as shown in Figure 4.

Figure 4

Beneficiaries



Notes. 4A–Companies, 4B–Government, 4C–Person and 4D–Does not apply.

From these conclusions, we arrive at the following questions:

- G6: *What benefits do companies and business owners gain from the integration of GenAI applications into their businesses?*
- G7: *Will beneficiary companies reduce costs by replacing human labour with machines?*

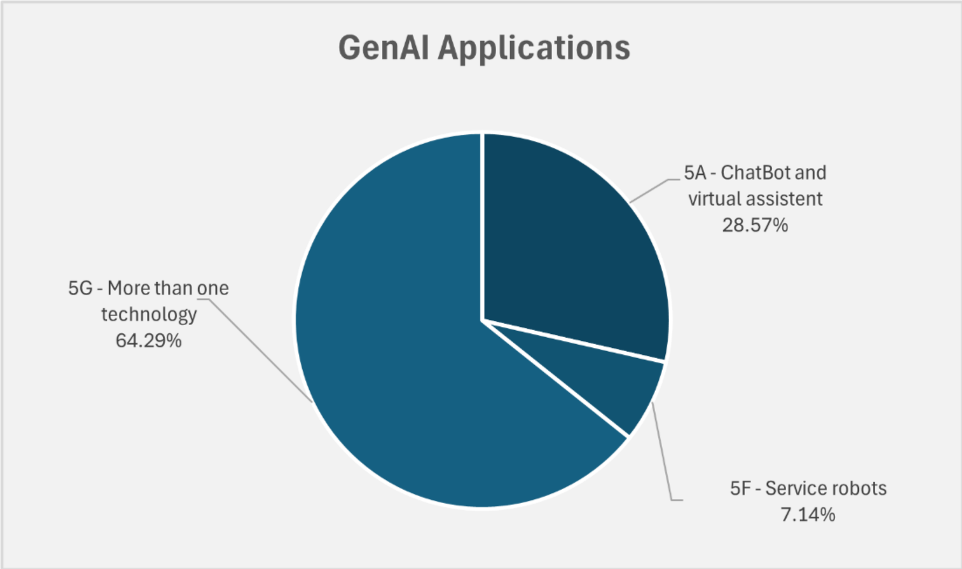
The classifications "4B–Government" and "4C–Individual" indicated a low level of only 3% each. This demonstrates the limited number of studies on individuals and governmental institutions benefiting from GenAI-generated social manipulation.

GenAI applications

This category presents some applications of GenAI and aims to identify which, among the variety of applications, are most used as instruments of manipulation. Figure 5 summarises the results covering six applications in three sub-categories: "5A–Chatbot and virtual assistant", "5F–Service Robots", and "5G–More than one technology". The sub-category with the greatest coverage, at 64%, was "5G". This sub-category indicates that most of the chosen and classified studies used more than one AI application in their material, which could be a combination of two or more applications among the six selected. This highlights the superiority of these applications, which are often underestimated in terms of their capacity and performance.

Figure 5

GenAI applications



Notes. 5A–Chatbot and virtual assistant, 5F–Service robots and 5G–More than one technology.

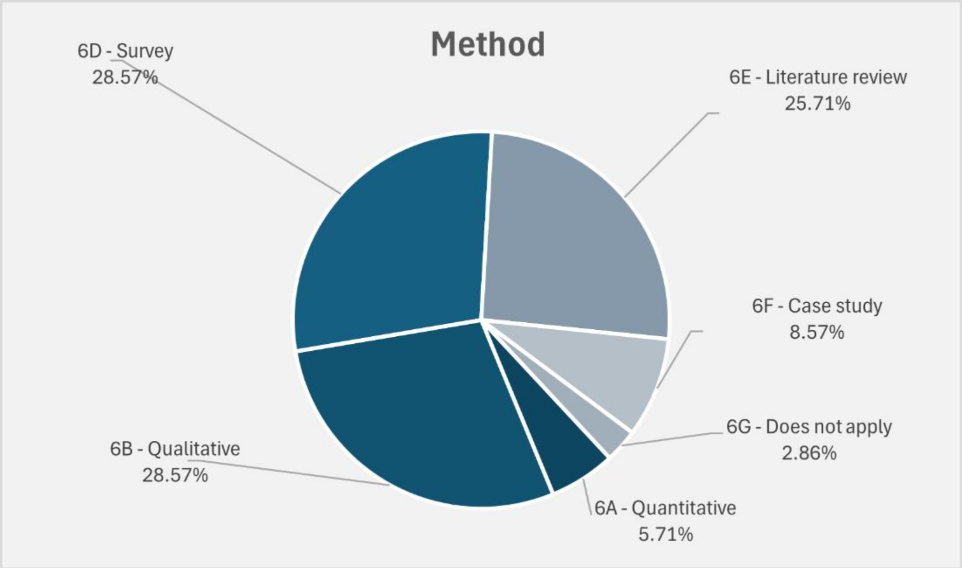
On the other hand, the lowest result was for the sub-category “5F”. However, this does not indicate that service robots were rarely mentioned in the selected studies. Their presence, in most cases, was associated with other AI applications that received different classifications and were rarely mentioned in isolation.

Method

An analysis of the research methods used in the investigation of GenAI’s dark side allows us to identify both the methods most commonly employed and those still underexplored. The latter represents a research gap that can be further investigated in future studies. Figure 6 presents the classification and statistical coding data of the analysed articles, providing a clear visualisation of the different research methods adopted in these investigations.

Figure 6

Method



Notes. 6A–Quantitative, 6B–Qualitative, 6D–Survey, 6E–Literature review, 6F–Case study, 6G–Does not apply.

The most significant codings were “6B–Qualitative” and “6D–Survey”, both with 28% coverage, indicating that the articles developed the theme more effectively through interviews and qualitative research methods. The study also found 25% of the articles classified as “Literature Review”, demonstrating a prevalence of theoretical research on this topic. However, contrary to this prevalence, we identified a lower volume of research using the quantitative method, with this method representing only 5%. This indicates a lower interest in research that employs the collection and analysis of numerical data to explain phenomena, test hypotheses, and establish statistical relationships. These conclusions and results allowed us to identify the following gaps:

- G8: *Why is there a certain lack of analytical and quantitative research regarding the consequences of the dark side of AI?*

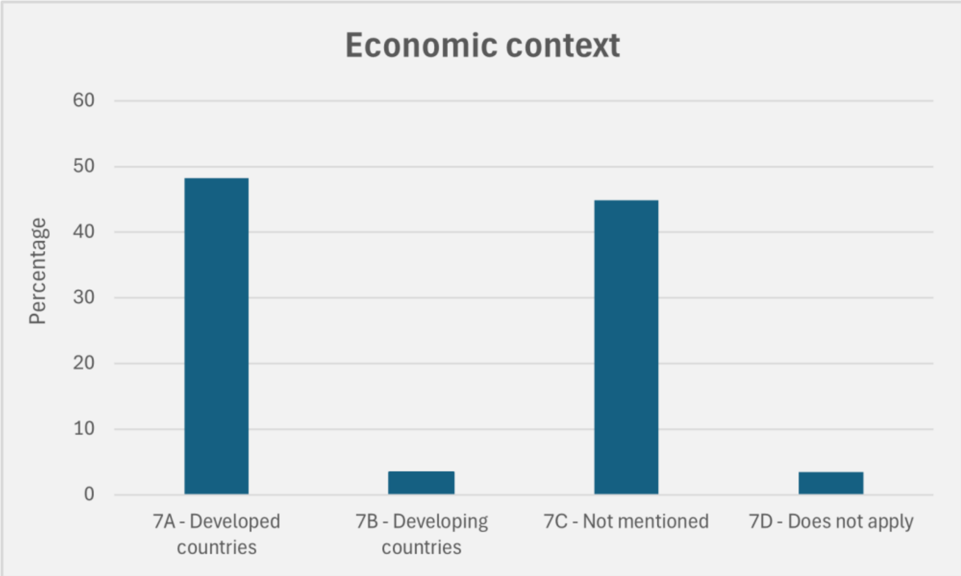
Economic context

The data presented in Figure 7 indicate that the coding “7A” accounts for 48%, demonstrating that most of the research is set in an economic context of developed countries.

This may indicate the superiority of developed countries in technological advances and investments compared to developing countries. The less expressive result concerning developing countries may suggest that access to GenAI applications is not equally distributed.

Figure 7

Economic context



Notes. 7A–Developed countries, 7B–Developing countries, 7C–Not mentioned, 7D–Does not apply.

The sub-category "7C–Not mentioned" has a coding value of 44%. This could be explained by the lack of this information in a significant number of studies, such as literature reviews. Given this context, the gap we identified can be summarised as follows:

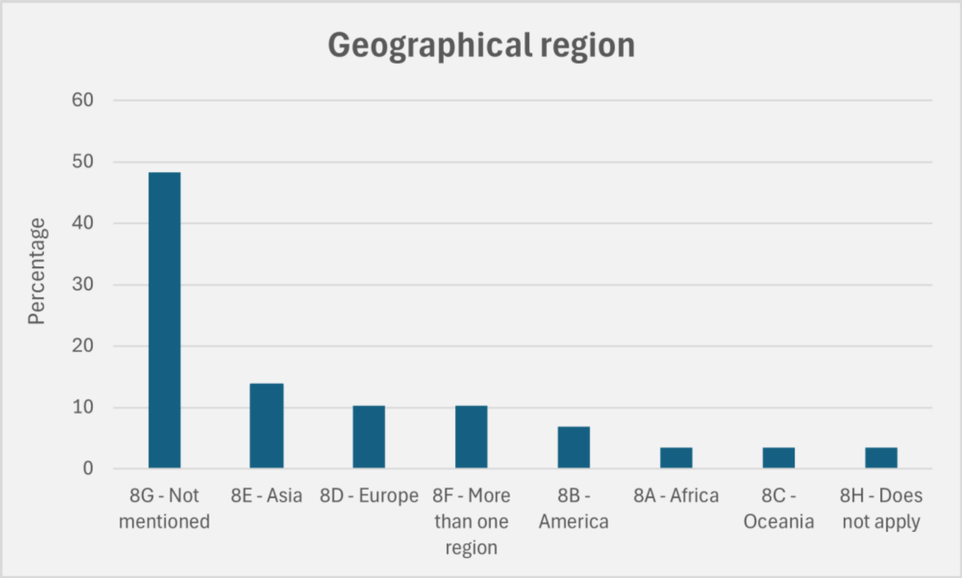
- G9: *Could access restrictions to GenAIs exacerbate the existing differences between developed and developing countries?*

Geographical regions

The geographical regions were divided by continents to ensure that this classification would be more synthesised. Consequently, the most frequently used region in the studied articles was "8E–Asia", which had a percentage of approximately 13%, as indicated in Figure 8. Similar to category 7, many studies do not indicate or provide location information. Consequently, many studies were classified under the category "8G–Not mentioned".

Figure 8

Geographical region



Notes. 8A–Africa, 8B–America, 8C - Oceania, 8D–Europe, 8E–Asia, 8F–More than one region, 8G–Not mentioned, 8H–Does not apply.

On the other hand, regions such as Oceania and Africa are rarely considered in the research. In this regard, as listed in G10, there seems to be a gap in the literature regarding studies that consider the economic, cultural, or religious characteristics of these regions.

- G10: *Why is the research on the dark side of GenAI limited, considering or observing the particularities of Oceania and Africa?*

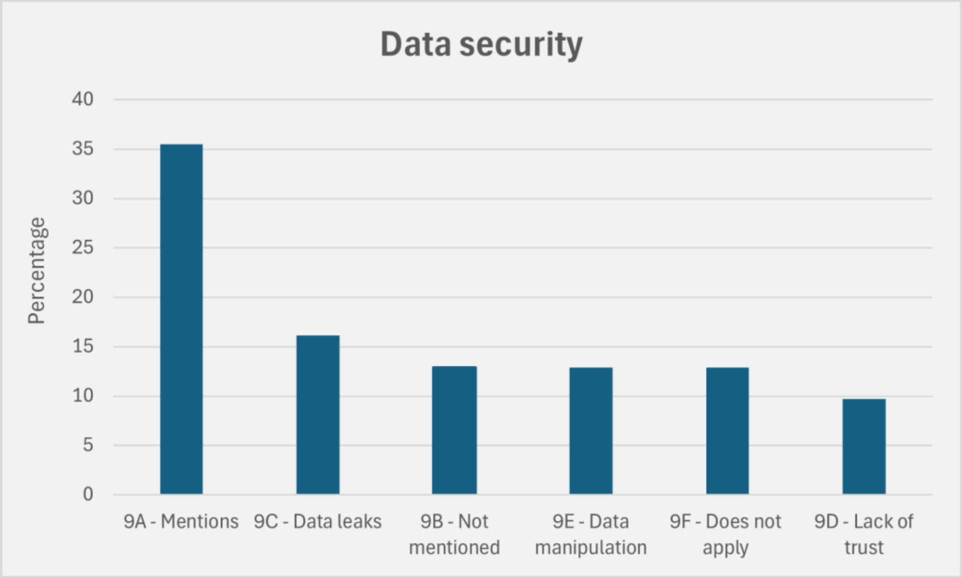
Data security

A recent research by Hu and Min (2023, p. 1) mentions a case regarding the identification of a user data security failure at a prestigious hotel in Japan, known for being one of the first hotels to employ a robotic staff. Cases like this are becoming more common, and concerns about data security and consumer and client privacy are increasingly being highlighted in recent studies. This category encompasses and brings together important concepts mentioned in classified research, such as "Lack of trust", used by Grewal, Guha, Satornino, and Schweiger (2021, p. 231).

Based on this context, after coding, it was observed that 35% of the classified articles mention the topic “Data Security” or “Data Privacy”. Consequently, the coding “9A” was the sub-category with the highest representation in the data security category, as shown in Figure 9. This result was expected, as clearly highlighted by Grundner and Neuhofer (2021, p. 3), given that this concern is frequently reported by users regarding their data.

Figure 9

Data security



Notes. 9A–Mentions, 9B–Not mentioned, 9C–Data leaks, 9D–Lack of trust, 9E–Data manipulation, 9F–Does not apply.

From another perspective, the least observed sub-category was “9D – Lack of trust”, with 9%, while “9B – Not mentioned” and “9F – Not applicable”, when combined, accounted for almost 26%. This result indicates that, although many studies highlight the importance of data security, few studies address this issue, which, in turn, results in the following gap:

- G11: *How can users monitor or gain control over their information when it is entered into GenAIs?*

Conclusions

AI, and specifically GenAIs, has already become a constant feature of contemporary society. Their applications are expected to increase in the near future, as well as diversify across multiple domains, influencing social dynamics, economic activities, and organisational practices in ways that demand careful examination by both researchers and policymakers. Given this scenario or certainty, this research aimed to identify common points about the dark side of GenAIs already evidenced in recent research. To accomplish this, we utilised the five-step method and investigated these studies to identify common points in the literature, represented by the sub-categories with greater representation in the categories we established, as well as gaps that, in turn, represent opportunities for future research.

Although we categorised the analysis of the studies to provide a clearer understanding of the diverse impacts of GenAIs on society, a recurring conclusion emerged across most of them: the digitalisation of tasks enabled by GenAIs is expected to profoundly influence the labour market. This finding underscores the need to regard this issue as a central theme in future academic discussions and empirical investigations. Finally, we acknowledge that our study has limitations, such as the number of studies and the bibliographic database considered; however, this point can be further addressed in future research.

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