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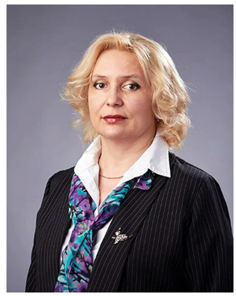

Utilizing Generative Artificial Intelligence for Sociological Studies

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This article examines the potential applications of generative artificial intelligence (GAI) in sociological research, in particular, in the analysis of text and images in various fields, including computational, qualitative and experimental research. The possibility of using free and commercial neural networks (using the example of *Fooocus*, *DALL-E*, *Perplexity* and *ChatGPT*) for text processing, image-to-text and text-to-image conversion in sociological research is demonstrated. GAI can increase the efficiency, flexibility, and accessibility of advanced computing techniques in these areas. A number of issues related to these technologies are noteworthy, such as interpretability, transparency, reliability, reproducibility, ethical aspects and privacy issues, as well as the consequences of bias and efforts to eliminate it. A separate problem is the formation of a sample of source objects for machine learning, since the sampling feature will affect the resulting objects obtained during the generation process. In addition, trade-offs between proprietary models and open source alternatives are discussed. When used rationally, these technologies can significantly advance various aspects of sociological methodology, complementing and enriching existing tools.

***Keywords*:** generative artificial intelligence, machine learning, text processing, image-to-text, text-to-image, sociological methodology, sociological studies.

Introduction

The explosive growth in the capabilities and popularity of neural networks after 2020 has caused great interest in generative artificial intelligence (generative AI, GenAI, or GAI), which is widely discussed in the media [*Kopyrin*, 2023] and causes a whole range of emotions from delight to serious concerns [*Harrington*, 2024]. Some researchers warn of possible catastrophic consequences, including a threat to humanity [*Ilichev*, 2023], while others point to the risk of creating malicious content and environmental costs [*Gluhih*, 2022]. In the colleges and universities, teachers face the problem of GAI when students pass off the results of neural networks as their own. It is important to consider the impact of these technologies on sociological research, as GAI can contribute to progress in text analysis, experiments and modeling.

This paper presents research at the intersection of social sciences and information technology to demonstrate the application of GAI in sociology. Two main methodological areas are considered: text and image analysis. First, large language models (LLM) improve the sociological analysis of textual data by offering more accurate classification of documents and opportunities for experimentation. It is considered how these models can be adapted for qualitative text analysis, allowing for more interactive and interpretative research. Secondly, it examines how modern GAI models such as *Fooocus*, *DALL-E*, *Perplexity* and *ChatGPT* can analyze, summarize, describe and generate text or images. It is shown how these models can encode visual data and create synthetic images for experiments. It is assumed that GAI complements, but does not replace, existing sociological methods.

Despite the potential of GAI, it is important to use these technologies carefully. The complexity of interpreting the output data, the opacity of the training data, and the possible unreliability of the results raise questions about reproducibility and privacy. These models also raise ethical concerns, especially in research related to personal data. The issue of GAI "bias" and its impact on social research is considered, as well as the need to develop models more suitable for the social sciences.

Artificial Intelligence to Analyze Texts Classification, Annotations and Methodological Recommendations

Large language models (LLM) is a type of artificial intelligence that specializes in processing and generating natural (human) language. They are machine models trained on huge amounts of text data, which allows them to "understand" questions and generate an answer in human language. Early versions of the models could not process voluminous input data and generated short sequences of text. A major breakthrough in overcoming these limitations occurred around 2023, with the advent of *ChatGPT* version 3 and the like. The rapid growth in the quality of responses from modern GAI is usually due to three factors: the development of computing power, the development of "transformers" — neural networks capable of processing long texts, and the availability of extensive texts for learning. Modern models are called "big" because of the huge amount of text they were trained on and the billions of parameters used to train them. For example, the Llama 3 model was trained on 15 trillion tokens and contains about 70 billion parameters.

The most relevant applications of large language models for sociological research are related to computational sociology. Sociologists use these models to classify texts, a task in which the model is trained to predict categories for new texts based on training data. This method is often used to process large volumes of texts, such as articles or social media posts. LLM surpasses traditional machine learning methods in text classification tasks due to pre-training on huge amounts of data, which allows them to adapt to new tasks without additional training.

LLMs are also able to speed up the process of annotating data. Recent research shows that LLMs can cope with the task of annotation, achieving quality on a par with people, significantly reducing costs. However, like humans, models can make mistakes or misinterpret instructions. Combining the work of people and LLM helps to improve the annotation process and reduce its cost.

The application of LLM goes beyond the classification of texts. Their versatility allows them to be used in various analysis tasks, for example, in thematic modeling or as probabilistic language models. The ability to work with queries allows scientists to create customized solutions without deep knowledge of computer science, which speeds up prototyping and research analysis. LLMs can be used to identify themes in texts or to verify various encoding schemes, as well as for confirmatory analysis. Although LLMs are not always the ideal tool for all text analysis tasks, their versatility creates opportunities for methodological innovation.

Conversational Computational Content Analysis

LLM promises to strengthen the use of computational methods in qualitative research. Qualitative researchers demand more rigorous, transparent and flexible content analysis procedures and suggest using computational methods to achieve these goals. LLMs are advantageous for qualitative analysis compared to traditional methods. Standard approaches, such as thematic modeling, work better with large amounts of data, and high-quality data, such as interviews or field notes, contain several elements that are difficult to analyze without losing information. LLMs, having extensive language representations, can directly analyze such texts without preprocessing. In addition, their flexibility allows you to adapt queries to specific data.

The most significant innovation is the possibility of interactive computational content analysis. LLMs allow researchers to “ask questions” about their data. For example, the model can summarize interviews, highlight topics, and analyze patterns. This differs from traditional qualitative analysis, which begins with a thorough reading of documents and the creation of thematic categories. LLMs change this process by iterating between computational and interpretive approaches, allowing interpretation to be distributed between humans and machines. The researcher interprets the model’s responses and can challenge or refine them with further queries.

This dialogic technique raises new questions. LLMs can use external knowledge gained during the training phase, which makes it more difficult to understand their interpretation of the data. It is important to examine the “preset assumptions” that influence the models’ responses. For example, models can reflect societal cognitive patterns and even reproduce stereotypes. To solve these issues, models are adapted using feedback from people, guiding them to certain values.

Researchers should experiment with query formulation to understand how models respond and compare the results with manual examples for validation. It is important to take into account not only your position in the study, but also the role of the model, analyzing the views embedded in it. Models should not be perceived as objective or neutral; their conclusions depend on the data they are trained on.

Contemporary high-quality projects often include a large number of interviews or observations and combine them with other data sources for mixed analysis. LLMs help high-quality researchers analyze data more efficiently and on a large scale, while maintaining interpretative nuances that may be lost when using traditional methods.

Multimodal Models to Analyze and Generate Visual Data Description

In addition to working with texts, AI opens up new opportunities in the sociological research of images and visual data. In parallel with the development of language modeling, computer vision has advanced significantly due to increased computing power and the development of convolutional neural networks (SNN) that can recognize complex patterns in images such as contours, textures and shades. Like LLM, computer vision models are pretrained on common sets of images and then adapted to specific tasks. These models have been successfully applied in sociological research, for example, to identify images related to protests on Chinese social media, or to analyze urban features such as trash on the streets according to Google Street View.

The new AIS are multimodal, which means that they are trained on different types of data, such as texts and images, and can use them as input and output data. This opens up unique opportunities for working with visual data, as text queries can be used to analyze images without additional configuration.

An example related to social movements shows how AI can extract information from images. For example, you can send a photo of the protests in Iran to GAI. As you know, on September 16, 2022, after the news of the death of Mahsa Amini, who was allegedly beaten by members of the Edifying Patrol after being arrested for "inappropriate wearing of the hijab," mass protests and riots against the country's state system began in Iran.

Fig. 1. The original photo for analysis

The *ChatGPT-4* toolkit, the o1 model, was used to analyze the photo. A fragment of the *ChatGPT-4* dialog is shown below.

Authors: Describe the picture attached.

ChatGPT: The image depicts a protest scene. In the foreground, there is a woman whose face is painted with the colors of the Iranian flag (green, white, and red). The red paint seems to drip down like blood, symbolizing violence or struggle. The word “Iran” is written on the white part of her face. Behind her, other protesters can be seen holding Iranian flags, and some have raised their fists in the air, a common gesture of defiance or solidarity during protests. The scene suggests a protest related to Iran, potentially linked to political or social unrest.

Authors: List the objects in the photo, select the description categories and convert the response to JSON format.

ChatGPT:


```
{
    “foreground”: {
        “person”: {
            “gender”: “female”,
            “face_paint”: {
            “colors”: [“green”, “white”, “red”],
            “symbolism”: “Iranian flag”,
            “detail”: “red paint resembling blood drips”
        },
        “text_on_face”: “Iran”
    }
},
“background”: {
    “protesters”: [
        {
        “gender”: “female”,
        “object”: “flag”,
        “flag_description”: {
        “country”: “Iran”,
        “colors”: [“green”, “white”, “red”]
        }
    },
        {
        “gender”: “multiple (male and female)”,
        “gesture”: “raised fists”
        }
    ]
},
“objects”: [
        {
        “name”: “Iranian flags”,
        “count”: “multiple”,
        “colors”: [“green”, “white”, “red”]
        },
        {
    “name”: “smartphones”,
    “count”: “multiple”,
    “usage”: “recording or taking pictures”
            }
    ]
}
```

The initial request was simple and did not disclose any information about the photo. The neural network's response showed that the model recognized the protest image and described the situation, the protesters, and even the text. To get more accurate data, a request was made to extract detailed information from the photo and present it in JSON format to facilitate subsequent processing, for example, in Python. As you can see, the neural network was able to recognize the text from the posters; it was possible to obtain structured information, often necessary for further statistical and computational research. Note the term "resembling," it shows the outstanding level of "understanding." The results were not perfect: some texts were not recognized, due to the fact that some inscriptions partially overlap. Apparently, refining queries or refining based on examples could improve accuracy.

This example highlights how a multimodal AI can encode and describe images without the need for specialized training. This approach can be scaled to analyze large sets of images, expanding the possibilities of studying collective actions using visual data. Unlike existing applications of computer vision in sociology, which are often limited to image classification or object detection tasks, multimodal AI can extract more complete information from visual data. Just as in the case of text analysis, interacting with models through queries simplifies experiments and creates new opportunities for using visual data in qualitative research. For example, ethnographers or archival researchers could use computer vision models to create descriptions of photographs or videos, which would simplify working with large collections of images and videos.

Synthetic Images Generation

LLMs can generate texts, and the most advanced multimodal models are able to generate images based on text queries. These synthetic data represent something new that goes beyond the usual categories. Like specially collected data, queries can adapt the generated materials to our requirements, but the resulting synthetic images may also be of interest, since they are synthesized based on huge amounts of data used to train models.

Until recently, texts and images generated by AI were considered a curiosity and could cause a smile or bewilderment, but technological progress has led to significant improvements in the quality of results. Texts created by LLM are difficult to distinguish from those written by humans [*Clark*, 2021], and images of faces generated by AI may be indistinguishable from real ones [*Wang*, 2024].

AI's ability to create realistic texts and images opens up new possibilities for experimental research. In particular, you can use tools like *Fooocus* or *DALL-E* to create realistic synthetic images, for example, to illustrate articles or statistical diagrams. Such images can improve the external validity of experiments by conveying social information in a more natural way than traditional attribute tables used in market research.

In the course of this work, in order to illustrate the capabilities of GAI, photorealistic images were synthesized using the *Fooocus* toolkit, the server part of which was launched in *Google Colab*. Only the models connected by default are used. To get the image (Fig. 2), the prompt was used: "A typical portrait of a girl in Iran at a protest demonstration." Additionally, parameters about a person's gender, age and emotions were transmitted to create images of two fictional characters.

Fig. 2. The result of image generation. Prompt parameters:
"woman, 30 years old, tense" (left) and "woman, 20 years old, calm" (right)

The resulting images are very plausible, although some inconsistencies in geometry can be noticed, and show differences in emotional expression and age. Even relatively simple queries allow you to generate images that convey a lot of information that can have an emotional impact on the viewer. It is interesting to note that the images include many details, such as clothing, facial expressions, and surroundings, which were not explicitly set, but were added by the neural network; at the same time, more detailed queries can explicitly control such elements.

When using models for analysis or image generation, it is important to take into account bias in the training data, which can lead to the model displaying some characteristics better than others. Like LLM, multimodal models acquire a certain "vision" and description of the world after preliminary training. Computer vision models often make mistakes in determining demographic data based on images, which leads to systematic biases against marginalized groups [*Buolamwini*, 2023]. These biases are also found in GAI: in particular, an audit of the Stable Diffusion model revealed the tendency of the model to reproduce stereotypes, including the representation of female faces when requesting an image of an "emotional person", white people when requesting an "attractive person" and black men when requesting a "thug" [*Bianchi*, 2023]. Given such nuances, it can be recommended to conduct additional research to assess the quality of these representations and hidden biases in order to confirm the possibility of using synthetic content in experimental conditions. In addition, attributes such as language proficiency or length of residence [*Flores*, 2018] are not always easy to visually represent, which limits the applicability of the generated images depending on the research question.

In addition to creating images of people, multimodal models can generate scenarios representing contextual and environmental factors, as well as large collectives. An example based on recent experiments to assess the impact of protest characteristics on their support

[*Bailey*, 2023] illustrates the possibility of using such models to create high-quality images of various demonstrations, protests and tactics. In this case, four images of protests were generated with variations in number, while keeping the venue and theme unchanged. In Fig. 3. you can see synthesized images for the query "Small rally of the Movement for Women's Rights in Iran," and in Fig. 4. synthesized images for the query "Mass demonstration of the Movement for Women's Rights in Iran."

Fig. 3. Two versions of synthesized images on request
"A small rally of the Movement for Women's Rights in Iran"

Fig. 4. Two versions of synthesized images for the query
"Mass demonstration of the Movement for Women's rights in Iran"

Indeed, all the images mentioned above show groups of protesters on the streets of Iran during the daytime. There are differences in the number of protests and in the location of the “virtual camera.” Protesters at a small rally hold placards with inscriptions that closely resemble the writing of Farsi (Iranian language). Many participants wear a hijab (they have their head covered). The flags of Iran are shown very plausibly. It is difficult to assess the nationality of the synthesized characters, but they quite resemble the average residents of Iran. There are also obvious disadvantages: image generation models cannot yet cope with the display of text, and some posters obviously contain meaningless inscriptions. Therefore, it is important for researchers to carefully check the generated content, although this problem will probably be solved as technology develops.

Although it is possible to solve the problems of synthetic media by selecting photos of real protests, the approach presented here allows you to create counterfactual scenarios that cannot be found among existing images. To demonstrate this potential, an image was generated of a demonstration of the Women’s Rights Movement in Iran with a burning car symbolizing the destruction of property and violence, which are known to reduce support for protests [*Buolamwini*, 2023], although such actions are not typical for women’s protests. This example uses the *Fooocus* model; the final version of the request is indicated in the caption to the image (Fig. 5). Obviously, this example clearly demonstrates how easy it is currently to mislead the reader or viewer by offering a photorealistic photo with a distorted meaning.

Fig. 5. Two versions of synthesized images on request
“Demonstration of the Movement for Women’s rights in Iran. A burning car in the foreground”

Multimodal models open up new possibilities for using visual data in sociology. These models are not only capable of performing classification tasks, but can also create detailed descriptions of images and generate realistic images reflecting sociologically relevant information. GAI’s textual, visual, and multimedia capabilities provide sociologists with new ways to interact with texts, images, and other media. This does not mean that all sociological research should use these tools, or that GAI will replace other computational methods and the role of the analyst, but technological innovations have unique capabilities that complement existing methodologies. GAI promises to make existing methods more flexible and effective, as well as open up new forms of analysis, computer interpretation and experiments with synthetic content.

Possible Problems with Using GAI

Regarding neural networks and artificial intelligence, general concerns are often expressed — concerns about the potential abuse of generative AI, such as cybercrime, the use of deliberately false news or the generation of video clips with the substitution of characters' faces (deepfake) for deception, fraud or manipulation of people [*Ilichev*, 2023], as well as the massive replacement of jobs by people [*Kopyrin*, 2023]. But if we focus on the application of GAI to solve applied problems in the fields of sociology, then the set of problems can be localized, which is discussed below.

Although GAI opens up methodological possibilities, these technologies face challenges of interpretability, transparency, reproducibility, reliability, and ethics. The scale of the models, while providing high performance, is also a source of weaknesses. Interpreting complex neural networks is difficult, especially models with billions of parameters. The field of "mechanical interpretability" tries to explain the work of such models, but it is at an early stage of development.

One of the most serious problems is that modern artificial intelligence (AI) models for image generation are better able to cope with the topic on which they have learned the most. Let's look at what causes this. First, these models are trained on huge datasets that include millions of images and corresponding text descriptions. This learning process allows them to identify complex relationships between words and visual elements. For example, when a model learns from images and text descriptions, she begins to understand what a "blue sky" or "green grass" is and how these elements usually appear together in real scenes. Secondly, modern approaches to AI training, such as contrastive learning and the use of synthetic images, allow models to better understand high-level concepts, rather than just memorize individual pixels. For example, the *StableRep* system, developed by researchers at MIT, uses synthetic images generated by text-image models to train models, allowing them to better understand concepts and variations rather than just data. Thirdly, models trained on a specific topic can better fill information gaps using general knowledge about the world. For example, if the model is trained on animal images, it can generate an image of a "pigeon on the street," taking into account that pigeons are usually gray, and streets often have certain architectural features.

There is also a problem with the transparency of training data, as many models are managed by corporations that do not disclose information about their data. This makes it difficult to assess the impact of the training data on the results. For example, synthetic images of protests during 2021–2022 may display masked participants due to data collected during the pandemic, which may introduce undesirable distortions when using these images in experiments. Therefore, it is important to consider how the training data can affect the results, and carefully evaluate them. In the long term, it is necessary to examine the data used for training in order to better understand the relationship between the inputs and outputs of the models.

GAI-related issues include reproducibility. Although the reproducibility of computational approaches is often considered a strength compared to the humanities, it is not guaranteed due to the stochastic structure of the models. Identical queries can produce different results, and similar reproducibility problems arise even in simpler machine learning models. In addition, GAI technologies controlled by corporations are subject to change without notice, which makes it impossible to reproduce previously obtained results.

The ability of GAI to generate a plausible conclusion may also adversely affect some studies. Models, as a rule, are not based on formal logic and can produce unreliable information, which raises concerns about reliability and stability. GAI developers are working to create more reliable models, but researchers should carefully check the findings and avoid using these models for tasks that require actual accuracy.

The use of GAI in social sciences raises new ethical and confidential issues. For example, working with sensitive data, such as interviews, may violate institutional review board (IRB) rules, since entering data into commercial models means that data is transferred to a third party. In addition, GAI can produce unexpected responses under experimental conditions, which can lead to racist or sexist stereotypes that negatively affect participants. Universities and the IRB should develop protocols for the safe use of GAI in research involving humans. Researchers should be aware of the risks associated with these technologies and carefully assess how the use of GAI may affect research subjects.

The Impacts of Bias and the Efficacy of Mitigation Efforts

The problem of bias in GAI models requires more careful consideration. Research shows that traditional machine learning methods can reproduce biases and stereotypes. For example, models trained to recognize gender from images are less accurate for black women, since the training examples predominantly contained white men [*Buolamwini*, 2023]. GAI also suffers from bias, which is associated with the use of a large amount of unconfirmed data [*Ilichev*, 2023]. This may have a negative impact on the social sciences; for example, for queries related to Muslims, the *ChatGPT* version 3 neural network often generated responses related to terrorism [*Buolamwini*, 2023].

AI development companies try to minimize the risk of bias by identifying problematic content and using additional instructions to avoid such conclusions. For example, OpenAI has changed the *DALL-E* model by adding demographic information to queries to increase the variety of output data. However, such measures can lead to absurd and historically inaccurate images.

Despite the importance of efforts to reduce bias, they can undermine the use of GAI in research. From a social scientific point of view, the ability to generate "biased" texts or images often makes them analytically useful [*Argyle*, 2023]. For example, restrictions on adult content or illegal activities may interfere with the analysis of interviews related to sexual health and drugs. In particular, the *DALL-E* 3 neural network refused to show immigrants with criminal records or violent protests. However, the *Fooocus* neural network had no restrictions on this topic. This situation highlights the obvious tension between bias and its mitigation. If bias is an issue, researchers may prefer more controlled models, such as Claude from Anthropic, which aim to be "helpful, honest and harmless."

Regardless of how GAI is used in sociological research, it is important to carefully check how the biases embedded in these technologies can affect the performance of specific tasks.

Leading scientists in the field of information technology have proposed to include documentation for models and training datasets (15), indicating known or hidden biases. However, such documentation should only be a starting point in studying the interaction between models trained on huge datasets and sociological data. Researchers should report any such problems in published papers, detailing where problems have been noticed, similar to how qualitative researchers reflect on their positionality and biases. If GAI are used to encode texts or visual data, we should evaluate their biases in the same way as we evaluate the work of a research assistant, carefully checking and comparing their findings with other examples. This verification is critical to ensure that research using these technologies is not only methodically innovative, but also ethically sound and scientifically reliable.

Comparison of Open-Source and Commercial Models

In addition, it is interesting to consider the comparison between two types of GAI models: open source and commercial, as well as their implications for sociological research. Currently, the most powerful models are being developed by commercial companies such as *OpenAI* and *Google*. The key features of these models, including internal parameters, architecture, and training data, are proprietary to the companies. In contrast, models such as *Fooocus* or *BLOOM* are open source, and anyone can familiarize themselves with the source code and input data.

From a technical point of view, closed models run by multiple corporations are usually more powerful and easier to use than open alternatives. For example, you can interact with *ChatGPT* through a browser, and software interfaces (APIs) allow users to pay for the execution of large volumes of requests. However, such models can be prohibitively expensive for applications that require large amounts of inference, for example, to classify text in millions of documents. Open models are starting to compete with commercial solutions, especially since companies like *Meta* and *Google* are opening up some of their models to the public, but these models often require access to expensive technical infrastructure, which makes them inaccessible to most sociologists.

Closed commercial models are now a more viable solution for many social scientists, but there are several reasons why open models should be preferred. Open models are not necessarily easier to interpret, but the source code and weights of the model are available, allowing researchers to try to interpret them. In addition, the transparency of the training data makes it possible to better assess potential biases and stereotypical conclusions. The ability to run these models on researcher-controlled hardware makes open models more compatible for the purpose of reproducibility, as researchers can store and share accurate model configurations. This eliminates privacy risks because data is not shared with third parties, making these models suitable for sensitive data tasks. With regard to bias, open models that can be freely modified are preferable if research is hampered by efforts to eliminate bias. In general, I encourage researchers to consider these issues carefully and recommend experimenting with several different models to test how different implementations affect task performance.

In the long term, it can be assumed that academic researchers will be better provided with the use of GAI, specially designed for scientific purposes, and will not have to rely on large corporations. Such models can eliminate the limitations of existing technologies, allowing proven researchers to assess the relationship between different training data and results, as well as generate more sensitive conclusions with fewer limitations.

Creating a GAI for the social sciences will require significant resources to collect and curate huge amounts of training data, as well as to manage and maintain the expensive equipment needed to train and deploy them. These initiatives are likely to go beyond the capabilities of a single group of researchers and require collaboration between multiple institutions. It is critically important that sociologists participate in these efforts both to analyze the social consequences of these technologies and to use their potential for the benefit of sociology.

Conclusion

In the public sphere, GAI is highly controversial. This article offers a more balanced approach, emphasizing the methodological possibilities that technological innovations open up, while recognizing their limitations. LLMs can surpass existing text classification methods, making them more efficient and accessible, as well as easily adapt to various fields and tasks. These same models can be used for more conversational content analysis, allowing qualitative researchers to interact with data in new ways.

There are other possibilities, for example, multimodal models can generate high-quality images of people and protests, including counterfactual scenarios, which can be used in experimental studies. The ability to use complex computational methods with minimal training and technical knowledge, as well as adapt them to specific needs, will certainly contribute to the spread of machine learning in sociology.

The examples given in the article are far from exhaustive. Researchers are developing creative applications of these technologies in various fields of social sciences. For example, LLMs can fill in gaps in survey data, help conduct semi-structured interviews online, and build more realistic simulations. The analysis of multimodal data makes GAI particularly promising for studying huge volumes of online and digital texts, images, audio and video.

Studying the representations embedded in these models will also provide an inside look into culture and cognitive processes. These transformational capabilities go beyond methodology, as GAI can serve as "virtual scientific assistants," help teach coding skills, and even generate research questions. AI research will become an important area of sociological analysis as these technologies spread to various areas of social life. While these technological changes will bring many benefits, sociologists can lead efforts to identify how AI reproduces existing inequalities and creates new forms of social division.

The use of GAI in sociological research also raises significant problems, since the strengths of these models can be perceived as weaknesses. Large and complex models are difficult to interpret, it is not always clear how their conclusions depend on the texts and images used in the pre-training, and they can give unreliable or misleading information. Pre-education on large volumes of text leads to the assimilation and reproduction of biases, which can make it difficult to use them in the academic research environment. At the same time, efforts to mitigate bias become more complicated, since bias is often a key object of interest for researchers. Scientists using these tools should be particularly attentive to these limitations and carefully evaluate and document how they may affect the application of GAI to specific research issues. Special care should be taken when working with sensitive data or interacting with research participants.

Some of the problems of existing GAI implementations are compounded by the fact that the most powerful models are controlled by corporations that provide little information about the internal structure of their systems or the data on which they are trained. Open alternatives can partially solve these problems, but they are more difficult to use, requiring more complex computational training and resources.

In conclusion, it is important to emphasize that GAI will not replace the researcher or existing methodological tools. As research on the use of AI in the workplace and other fields shows, we should worry less about these technologies replacing us and focus more on their potential to empower us. Obviously, GAI can improve existing methodologies such as supervised text classification and data annotation, as well as enable new forms of research such as conversational content analysis and image synthesis. When used carefully, these technologies can contribute to methodological innovations in the social sciences and contribute to the formation of new subfields and specializations. Sociologists can be encouraged to take advantage of the methodological opportunities offered by GAI.

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Использование генеративного искусственного интеллекта для социологических исследований

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В настоящей статье рассматриваются потенциальные возможности применения генеративного искусственного интеллекта (ГИИ) в социологических исследованиях, в частности, при анализе текста и изображений в различных областях, включая вычислительные, качественные и экспериментальные исследования. Продемонстрирована возможность использования бесплатных и коммерческих нейронных сетей (на примере *Fooocus*, *DALL-E*, *Perplexity* и *ChatGPT*) для обработки текста, преобразования изображений в текст и текста в изображение в социологических исследованиях. Продемонстрировано, что ГИИ может повысить эффективность, гибкость и доступность передовых компьютерных технологий в этих областях. Заслуживает внимания ряд вопросов, связанных с этими технологиями, таких как интерпретируемость, прозрачность, надежность, воспроизводимость, этические аспекты и вопросы конфиденциальности, а также последствия предвзятости и перспективы ее компенсации. Отдельной проблемой выступает формирование выборки исходных объектов для машинного обучения, поскольку ключевые параметры выборки будут проявляться на результирующих объектах, полученных в процессе генерации. Кроме того, обсуждаются компромиссы между коммерческими моделями и альтернативами моделями с открытым исходным кодом. При рациональном использовании вышеописанные технологии могут значительно повысить эффективность различных аспектов социологической методологии, дополняя и обогащая существующий инструментарий.

***Ключевые слова*:** генеративный искусственный интеллект, машинное обучение, обработка текста, преобразование изображения в текст, преобразование текста в изображение, социологическая методология, социологические исследования.